

- 1 Article title: A comparative analysis of quantitative metrics of root architectural phenotypes
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- 5 One sentence summary: Metrics of phenes are more reliable, stable, and robust descriptions of root
- 6 architecture than are estimates of phene aggregates.
- 7 Number of Tables: 3
- 8 Number of Figures: 9
- 9 Abstract length: 244
- 10 Word Count: 6625

11 **Abstract**

12 High throughput phenotyping is important to bridge the gap between genotype and phenotype. The
13 methods used to describe the phenotype therefore should be robust to measurement errors,
14 relatively stable over time, and most importantly, provide a reliable estimate of elementary
15 phenotypic components. In this study, we use functional-structural modeling to evaluate
16 quantitative phenotypic metrics used to describe root architecture to determine how they fit these
17 criteria. Our results show that phenes such as root number, root diameter, lateral root branching
18 density are stable, reliable measures and are not affected by imaging method or plane. Metrics
19 aggregating multiple phenes such as *total length*, *total volume*, *convexhull volume*, *bushiness index*
20 etc. estimate different subsets of the constituent phenes, they however do not provide any
21 information regarding the underlying phene states. Estimates of phene aggregates are not unique
22 representations of underlying constituent phenes: multiple phenotypes having phenes in different
23 states could have similar aggregate metrics. Root growth angle is an important phene which is
24 susceptible to measurement errors when 2D projection methods are used. Metrics that aggregate
25 phenes which are complex functions of root growth angle and other phenes are also subject to
26 measurement errors when 2D projection methods are used. These results support the hypothesis
27 that estimates of phenes are more useful than metrics aggregating multiple phenes for phenotyping
28 root architecture. We propose that these concepts are broadly applicable in phenotyping and
29 phenomics.

30

31 Introduction

32 Crop production needs to double by 2050 to provide for the increasing global population (Tilman
33 et al., 2011; Ray et al., 2013; Wise, 2013; FAO, 2017). A major challenge is the identification of
34 efficient crops that cope with climate change and reduce the need for fertilizer and water inputs to
35 make agriculture environmentally sustainable. Root architecture influences water and nutrient
36 uptake, so, selecting and developing efficient crops based on their root system architecture (RSA)
37 has been proposed as a strategy towards a “second green revolution” (Lynch, 2007; Herder et al.,
38 2010; Villordon et al., 2014; Lynch, 2019).

39 Development of powerful tools in genomic research has resulted in a deluge of genomic
40 information. However, this genomic information cannot be fully exploited for crop improvement
41 unless it is linked to the phenome (Lynch and Brown, 2012; Cobb et al., 2013; Tardieu et al.,
42 2017). In the context of roots, the root phenome is the set of phenes manifested by roots of a plant,
43 where phenes are elementary units of the phenotype; phenes are related to phenotypes as genes are
44 to genotypes (Lynch and Brown, 2012; York et al., 2013). Phenotyping is a bottleneck for breeding
45 and genetic analysis because it is species-specific, labor intensive and environmentally sensitive,
46 unlike genotyping, which is uniform across organisms, highly automated, and increasingly
47 inexpensive (Furbank and Tester, 2011; Lynch and Brown, 2012; Cobb et al., 2013; Atkinson et
48 al., 2019). Phenotyping is especially challenging for roots because of their complexity, plasticity,
49 and inaccessibility. Significant advances are being made in phenotyping methods and technology
50 in an attempt to develop high-throughput platforms. In order to develop efficient strategies to
51 explore the phenome, it is important to clarify what constitutes a phenotype, delineate the key
52 components that comprise a phenotype, and determine the level of resolution at which phenotypic
53 data must be collected. Although an essentially infinite number of measurements may be collected
54 to describe each phenotype, a smaller number of more basic variables may explain most of the
55 important phenotypic variation among genotypes. These basic variables, or *phenes* are the
56 elementary units of the root phenotype and cannot be decomposed to more phenes at the same
57 scale of organization (Lynch and Brown, 2012). Based on this definition, number of axial roots,
58 lateral root branching density (LRBD), root growth angle, root diameter length of different root
59 classes of the root system can be considered as phenes.

60 Current methods for developing high-throughput phenotyping platforms and identification of
61 relevant quantitative trait loci (QTL) associated with traits of interest are largely based on non-
62 elementary phenotypic metrics. Non-phenes, referred to as phene aggregates in this paper, are
63 aggregate components of the root phenotype and describe the distribution of roots, shape of roots
64 and/or size of the root system. Phene aggregates include several conventionally measured traits
65 including *total root length*, *total area*, *total volume*, as well as novel phenotypic metrics such as
66 *convex hull volume*, *convex hull area*, *ellipse major axis*, *ellipse minor axis*, *ellipse aspect ratio*,
67 *volume distribution*, *solidity*, *bushiness* (Iyer-Pascuzzi et al., 2010; Clark et al., 2011; Cobb et al.,
68 2013; Topp et al., 2013) and metrics which measure the geometry and complexity of root systems
69 such as *fractal dimension* (FD), *fractal abundance* (FA), and *lacunarity* (Fitter and Stickland,
70 1992; Nielsen et al., 1999; Walk et al., 2004). Aggregate phenotypic metrics (referred to as
71 aggregate metrics) are comprised of phenes, some of these can be measured as a simple aggregate
72 of phenes (e.g. *total length*), some are represented as a function of other aggregates (e.g. *bushiness*
73 *index*, *solidity*, *volume distribution*), some measure shapes resulting from interaction of the
74 constituent phenes (e.g. *Convex hull volume*), and some metrics are complex metrics which

75 measure emergent properties of root architecture and cannot be described as a simple aggregate,
76 shape aggregate or a function of other aggregates (*e.g. Fractal Dimension*).

77 Estimates of phene aggregates change over time and are phenotype specific. Some phene
78 aggregates increase over time, some remain relatively static and some decrease in value over time
79 (Iyer-Pascuzzi et al., 2010; Zurek et al., 2015). The magnitude of change in estimates of phene
80 aggregates with time also vary greatly. This is because some of the phene aggregates are one-
81 dimensional measurements while some measurements are a function of more than one dimension
82 (Mairhofer et al., 2013). Many phene aggregates are estimates generated from the average values
83 of the 2D projections in a rotational image series (Topp et al., 2013) and are thought to represent
84 3D root shape accurately. However, which traits can be measured accurately using estimates
85 derived from 2D data and which require 3D representations is poorly understood. Depending on
86 the phenotype, metrics derived from rotated 2D projections of the same 3D root system can vary
87 significantly. This leads to a related question of how much should an aggregate phenotypic metric
88 differ for two phenotypes to be considered distinctly different. Fractal analysis of corn roots have
89 shown that the *FD* of two genotypes can be same but vary in *FA* (Eghball et al., 1993). Root
90 systems with similar *FD* may vary functionally and genotypes can be distinguished when fractal
91 analysis involves *FD*, *FA* and *lacunarity* (Walk et al., 2004). Aggregate phene metrics estimate
92 the aggregate of multiple phenes. For example, greater rooting depth is an important trait for
93 capture of subsoil N in maize. Greater rooting depth results from a combination of deeper axial
94 root growth angle (Manschadi et al., 2006; Trachsel et al., 2013; Uga et al., 2013), root elongation
95 rate (Manschadi et al., 2008), expression of fewer crown roots (Saengwilai et al., 2014b; Gao and
96 Lynch, 2016), reduced lateral branching density (Postma et al., 2014; Zhan et al., 2015), formation
97 of root cortical aerenchyma (RCA) (Postma and Lynch, 2011; Saengwilai et al., 2014a), reduced
98 cortical file number and increased cortical size (Jaramillo et al., 2013; Chimungu et al., 2014).
99 Each of these phenes are under distinct genetic control and have important interactions with each
100 other. Selection for combination of specific phenes will therefore be much simpler and precise
101 than would selection for root depth itself (Lynch, 2019). Phenens are under more simple genetic
102 control and permit more precise control over the root system architecture (RSA) and so, are more
103 useful for selection for crop breeding (Lynch and Brown, 2012; Lynch, 2019).

104 In this study, we use the functional-structural plant model *SimRoot* to identify phenotyping metrics
105 that are

- 106 • sensitive enough to provide information on the constituent root phenes and their states,
- 107 • stable over time and are independent of the time of phenotyping,
- 108 • robust to the imaging method *i.e.*, do not vary when measured in the intact 3D root system
109 or when estimated using 2D rotational image series.

110 Our analysis shows that

- 111 • Phene aggregates can be explained by phenes. Different phene aggregates capture different
112 combinations of subtending phenes. However, these metrics do not provide any
113 information or measure of the phene state of the constituent phenes.
- 114 • Several combinations of phenes in different states can produce phenotypes which have
115 comparable estimates of phene aggregates. Estimates of phene aggregates are not unique
116 representations of the state of the underlying phenes.

- 117 • As the number of phenes captured by an aggregate phenotypic metric increases, the
118 stability of that metric becomes less stable over time.

119 **2. Materials and Methods**

120 2.1 Simulation of phenotypes:

121 The functional-structural plant model *SimRoot* (Lynch et al., 1997) was used to simulate bean
122 (*Phaseolus vulgaris*) and maize (*Zea mays*) root phenotypes. In *SimRoot*, simulated root system
123 comprises of roots of distinct classes as specified by their root diameters, lateral root branching
124 density, root growth rate and root growth angle in the input parameters. The root growth angle
125 over time depends on the gravitropism. Stochasticity is included in all parameters. The roots are
126 simulated as small connected root segments over time. Co-ordinates corresponding to the root
127 being simulated as well as the root length, volume, area parameters are stored for the simulated
128 root segments as the root grows at specified time points. The root length, area, volume of the root
129 system is estimated by integrating the respective parameters over all root segments. The root image
130 co-ordinates are used to visualize the simulated root system.

131 The number of roots of different root classes, angle, diameter, lateral root branching density
132 (LRBD) were varied to produce 1500 maize root phenotypes and 1500 bean root phenotypes. The
133 range of values used for each of the root parameter used are given in Supplementary Material 2.

134 The data corresponding to the simulated root phenotypes were saved during the simulation runs.
135 These data files contained the X, Y, Z co-ordinates of the simulated root system images used to
136 simulate the root as well as data of root length, area, volume etc. of the simulated root segments
137 with their corresponding root class. Roots were allowed to grow without any boundaries so that
138 the growing roots did not touch any boundary surface and so no artifacts were introduced due to
139 mirroring roots. Stochasticity was included in all the simulated parameters. Root growth angle was
140 influenced by root gravitropism. In order to obtain accurate estimates of all the phenotypic traits,
141 elementary and aggregate phenotypic were extracted/calculated from the data of the simulated
142 images.

143 2.2 Measurement of phene and aggregate phene metrics

144 Estimates of phene metrics were measured from the simulated images. Aggregate phenotypic trait
145 metrics were calculated for intact 3D root systems as well as projections of the roots systems on a
146 2D plane. The root system was rotated by 20 degrees and the projections on a 2D plane were
147 obtained (Figure 1 and Supplementary Figure S1). The average of the estimates of each metric in
148 all the projected images for each phenotype was used in studies considering 2D projections. The
149 average value was used also in 3D studies where 3D estimates were not obtained including ellipse
150 major axis, ellipse minor axis and ellipse aspect ratio. The phene aggregates estimated and
151 considered in this study, the definitions of these traits and the method of obtaining those metrics
152 from *SimRoot* output is given in Table 1. In order to evaluate how phene metrics and phenotypic
153 trait metrics change over time, root images were obtained every 5 days starting 10 days after
154 germination and metrics obtained for these root systems. This way phenotyping metrics were
155 obtained for 3D root systems, 2D projections of the root systems, and root system images after
156 different periods of growth.

157 2.3 Random forest analysis

158 Data obtained from 3D root systems were analyzed using Random Forest regression. For metrics
159 where 3D metric data were not available (ellipse minor axis, ellipse major axis and ellipse aspect
160 ratio), the average value of the aggregate phenotypic trait from 2D rotational series was used.
161 Random Forest, is a nonparametric technique derived from classification and regression trees
162 (CART). Random Forest consists of a combination of many trees, where each tree is generated by
163 boot-strap samples, leaving about a third of the overall sample for validation (the out-of-bag
164 predictions – OOB). Each split of the tree is determined using a randomized subset of the predictors
165 at each node. The final outcome is the average of the results of all the trees (Breiman, 2001; Cutler
166 et al., 2007). It uses the OOB samples (independent observations from those used to grow the tree)
167 to calculate error rates and variable importance, no test data or cross-validation is required.
168 However, this method does not calculate regression coefficients nor confidence intervals (Cutler
169 et al., 2007). It allows the computation of variable importance measures that can be compared to
170 other regression techniques. The R package Random Forest was employed for the data analyses,
171 with $n_{tree} = 1000$ and $m_{try} = 8$. Random forest regression was used with each aggregate phenotypic
172 metric as the dependent variable and the input variables as the independent variables to identify
173 the most important variables. The selection of the most relevant variables to include in the final
174 model was done by ranking the variables according to their importance and excluding the least
175 important variables. The variable importance measure, the mean decrease in accuracy (%IncMSE)
176 was used for selecting the important variables. Variable importance is measured by mean squared
177 error of a variable p , which is averaged increase in prediction error among all regression trees
178 when the OOB data for variable p is randomly permuted. If variable p is important there will be
179 an increase in prediction error. Random forest was conducted 50 times and 90 percentile from
180 distribution of mean squared error as the significance threshold of individual variables. The
181 variables thus chosen were used to run a reduced variable model of the original random forest
182 model for each aggregate metric. The reduced variable models were deemed acceptable if the
183 Random Forest trained upon the most important descriptors gave a fit to the data set which was
184 similar or better than that trained upon all variables.

185 2.4 Variation in estimates of phenic aggregate metrics

186 One aspect of the study was to find if estimates of aggregate phenotypes were a unique
187 representation of the phenes. To address this, a representative phenotype was chosen for the maize
188 root system and phenotypes varying by less than 1 % of an aggregate phenotypic trait a shape
189 phenotypic trait (Convex hull Volume) and a complex phenotypic trait (FD) were chosen to find
190 if the phenes constituting the phenotype varied when the aggregate phenotypic trait was similar.
191 In an alternate approach, the estimates of convex hull volume and FD of bean root phenotypes
192 with differences in basal root whorl number and root growth angles with distinct functional value
193 (Rangarajan et al., 2018) were studied.

194 2.5 Estimates of phenic and aggregate phenic metrics obtained from 2D projections

195 In order to study the variation in metrics estimated in 2D rotational image series, the coefficient of
196 variation for each phenotype for each phenotypic trait metric was calculated from 2D projections
197 of the root system and the phenotypic metrics were compared.

198 2.6 Estimates of phenic and aggregate phenic metrics over time

199 Root system image data were saved every 5 days from day 10 to day 40 of growth and the 3D
200 estimates of the phenes and phenic aggregates were collected.

201 3. Results

202 Different bean and maize phenotypes were simulated by varying input parameters in *SimRoot*.

203 3.1 Variation in simulated phenotypes

204 The estimates of all phenotypes were min-max scaled and the phenotypes were clustered by
205 hierarchical cluster analysis of the phenotypes based on their phenes. The results of our study are
206 based on a wide array of phenotypes. Phenotypes included in the study had vastly different
207 phenotypes and differed in few or many phenes. The heatmap in Figure 2(a) shows a small subset
208 of data: the relative values of the bean phenes in a few phenotypes (rows) and the corresponding
209 phenotypes in Figure 2(b). Phenotype 1 had very shallow basal root growth angle compared to
210 phenotype 2 while phenotypes 8 and 9 had deep basal root growth angles. Phenotype 7 had more
211 basal roots than the other phenotypes. Phenotypes 5 and 6 differed in the basal root branching
212 density as well as basal root angle. The heatmap in Figure 3(a) shows a small subset of data: the
213 relative values of maize phenes in a few phenotypes (rows) and the corresponding phenotypes in
214 Figure 3(b). Phenotypes 2 and 3 differed in the number of nodal roots with phenotype 2 having
215 more nodal roots than phenotype 3. Phenotypes 4 and 6 had similar primary root lateral branching
216 but phenotype 6 had no seminal roots while phenotypes 4 had 5 seminal roots. Phenotypes 8 and
217 9 differed in the number of seminal roots as well as seminal root LRBD and the number of nodal
218 roots. The heatmap of all bean root phenotypes and representative phenotypes considered in this
219 study is included in Supplementary Figure S2(a) and S2(b). A similar heatmap for maize root
220 phenotypes are presented in Supplementary Figure S3(a) and S3(b) respectively.

221 3.2 Correlation among phenotypic metrics

222 Strong correlations were found among the phenes (Figure 4(a) and Figure 4(b)), in the bean root
223 system as well as the maize root system. Axial root length was negatively correlated with diameter,
224 number and LRBD of basal roots in bean and nodal roots in maize root system. The primary axial
225 root length and seminal axial root length was negatively correlated with diameter of the primary
226 root, seminal root axial root length was also negatively correlated with nodal root LRBD.
227 Phenotypes with longer axial roots had greater *maximum width*, *maximum depth*, *convex hull area*,
228 *convex hull volume*, *major ellipse axis*, *minor ellipse axis* but smaller values for *solidity* (Figure
229 4(b)). *Solidity* was positively correlated with diameter and number of basal roots in bean. Strong
230 correlations also exist between aggregate phenotypic trait metrics. *Major ellipse axis* positively
231 correlated with *maximum depth*. *Convex hull area*, *convex hull volume*, *minor ellipse axis* and
232 *maximum width* are highly positively correlated with each other. but are negatively correlated with
233 *solidity* (Figure 4).

234 3.3 Random forest analysis: Different phenes are important in determining the estimate of different 235 aggregate phenes

236 The results of the random forest analysis are shown in Table 2. Reduced variable models created
237 with Random Forest show proportion of explained variance (R^2) between 80 % and 99 % for
238 models with all aggregate phenotypic metric except *bushiness index*, which had 62 % in bean and
239 41% in maize; and *FD* which had R^2 of 67 % in bean and 20 % in maize. The most important
240 variables for each aggregate phenotype for the bean and maize models are summarized in Table 3.
241 The variables have been summarized based on the phene the variable represents.

242 Among the variables evaluated by the random forest analysis, axial root length and lateral root
243 length were found to be important explanatory variables for all the phene aggregates in both bean
244 as well as maize. Lateral Root Branching Density (LRBD) was found to be an important variable
245 for *total length*, *total area*, *total volume*, *maximum number of roots*, *median number of roots*
246 *bushiness index*, *FD* and *FA* in bean as well as maize. LRBD was also important for *volume*
247 *distribution* in maize root phenotypes and *ellipse aspect ratio* in bean root phenotypes. Number of
248 roots and diameter played important roles in determining the *total area* in maize and bean root
249 systems respectively. Root diameter was an important variable for *total volume*, *volume*
250 *distribution*, *maximum depth*, *solidity* and *FD* in both bean and maize phenotypes. Diameter was
251 also an important variable in *total area* and *ellipse aspect ratio* in bean and *bushiness index* in
252 maize root phenotypes. Angle was selected as an important variable by the random forest models
253 for *maximum width*, *convex hull area*, *convex hull volume*, *ellipse minor axis*, *ellipse aspect ratio*,
254 *solidity* and *FD* for both maize and bean. All the variables evaluated are important for the model
255 with *FD* as the dependent variable.

256 3.4 Estimates of aggregate phene metrics can be similar for phenotypes with different phene states

257 Even in phenotypes with similar estimates for aggregate phenotypic metrics, the phene states of
258 the constituent phenes varied greatly (Figure 5(a), Figure 5(b)). Phenotypes chosen based on the
259 similarity of aggregate phenotypic metrics had different diameter, LRBD, and number of roots of
260 different classes. Conversely, phenotypes in which phenes exist in different states have similar
261 aggregate phenotypic metrics (Figure 6). Four bean phenotypes that vary only in the number of
262 basal roots and root growth angle were chosen and the estimate of total volume, convex hull
263 volume and *FD* were compared (Figure 6). Phenotype 1 has one whorl of basal roots with shallow
264 angles, phenotype 2 has one whorl of basal roots with deep angles, phenotype 3 has three whorls
265 with fanned root growth angles. While phenotypes 1 and 2, which vary only in root growth angle,
266 have different estimates for all the three metrics considered (total volume, convexhull volume and
267 *FD*) phenotypes 1 and 3 have similar estimates for *FD* (varying by less than 2%) even though they
268 vary in both in number of basal roots as well as root growth angles. Similarly, phenotype 4 has
269 four whorls with fanned angles and differs from phenotype 3 and phenotype 1 in number of basal
270 roots as well as root growth angle, but varies in the estimates of total volume by 1% and 16 %
271 respectively; and in the estimate of convexhull volume by 1% and 4% respectively (Figure 6).

272 3.5 Variation in estimates of phene and phene aggregate metrics obtained from 2D projections

273 In order to study which metrics are not accurately represented by 2D projections, elementary and
274 aggregate phenotypic metrics were estimated from 2D projections obtained by rotating the root
275 system through 360 degrees at 20 degree intervals. It should be noted that *convex hull volume* and
276 area of a 2D projection corresponds to surface area of a 2D hull and the length of the perimeter of
277 a 2D hull respectively. Analysis with 2D image series shows that among phenes, estimates of root
278 growth angle differ when projections are obtained at different rotations. Among aggregate
279 phenotypic trait metrics, the metrics which have angle as one of the most important variables,
280 including *convex hull volume*, *convex hull area*, *minor ellipse axis*, *major ellipse axis*, *ellipse*
281 *aspect ratio*, *solidity*, *FD* and *FA*, as determined in the random forest analysis, are sensitive to
282 projection. These phenotypic metrics had a coefficient of variation of 10-20 % but some had much
283 greater CV depending on the phenotype in both the maize and bean (Figure 7(a) and Figure 7(b)).
284 The differences in estimates inflated when an aggregate phenotypic trait was calculated as a

285 function of two metrics which are already subject to lot of measurement variation (Figure 7(a) and
286 Figure 7(b)).

287 3.6 Variation in estimates of phene and phene aggregate metrics over time

288 Some phene aggregates such increase substantially over 30 days, while some remained relatively
289 static and estimates of some aggregate metric decreased with time (Figure 8(b), Figure 9(b)). Of
290 the traits, *total length*, *total area*, *total volume*, *maximum depth*, *convex hull area*, *convex hull*
291 *volume*, *major ellipse axis*, *minor ellipse axis* and *FA* progressively increased over time in both
292 bean and maize (Figure 8(b), Figure 9(b), Supplementary Figure S4(b), Supplementary Figure
293 S5(b)). There was only a small change in the *maximum number of roots* in bean over time but this
294 value increased significantly in maize over time (Supplementary Figure S5(b)). The pattern of
295 changes in *FD* over time was dependent on the phenotype. There was a small decrease in *bushiness*
296 *index* of bean over time (Figure 8(b)). In maize, the phenotypes showed a significant increase from
297 day 10 to 20 followed by a drop from day 20 onwards (Figure 9(b)). The magnitude of increase
298 was dependent on the phenotype. *Volume distribution* was either static or there was a slight
299 increase in the bean phenotypes over time (Supplementary Figure S4(b), Supplementary Figure
300 S5(b)). In maize the change in magnitude of *volume distribution* over time was dependent on the
301 phenotype.

302 Discussion

303 This study investigated the importance and utility of phenes and phene aggregate traits in
304 phenotyping studies. Our results confirm that phenes are robust and stable over time and also
305 sensitive enough to discriminate between highly similar root systems. In contrast, since phene
306 aggregates capture combinations of subtending phenes, and several combinations of phenes in
307 different states can produce phenotypes which have comparable estimates of phene aggregates, the
308 estimates of phene aggregates are not unique representations of the state of the underlying phenes.
309 Aggregate phene metrics are not stable over time, mostly because there is a rapid development of
310 many elementary root phenes over time. When the number of phenes estimated by the aggregate
311 metric increases, the complex interactions among phenes result in the same phenotype having
312 vastly different estimates for the same aggregate metric at different time points.

313 4.1 Root models can aid exploration of root phenomics

314 In this study we use *SimRoot* to simulate root systems and use the simulated phenotypes to evaluate
315 various root phenotyping metrics. We used modelling for this study due to constraints in obtaining
316 empirical data caused by limitations in phenotyping methodologies and artifacts due to
317 technicalities in image processing. Phenotyping efforts represent a compromise between
318 throughput, precision and data processing. Many high-throughput phenotyping methodologies
319 involve obtaining 2D metrics and depend on growing plants in controlled growth systems such as
320 pouch, pots, gel plate systems, germination paper, etc. where root architecture is affected due to
321 spatial growth constraints, in particular, branching angles. Not all 3D RSA estimates can be
322 obtained by series of 2D image data; some phenotyping metrics such as volume of non-convex
323 shapes cannot be obtained from 2D projections, especially from complex root systems. Occlusions
324 in 2D images caused by crossing roots increase complexity of systems and reduce accuracy of
325 many 2D estimates; this is especially true for mature root systems which are complex branched
326 structures composed of overlapping and crossing segments (Lobet et al., 2017) ; 3D estimates are
327 better for measuring these “traits” but are biased for other parameters such as surface area due to

328 technicalities in image reconstructions. 3D imaging techniques such as x-ray computed
329 tomography (μ CT) and magnetic resonance imaging allow non-invasive studying of
330 spatiotemporal dynamics of root growth (Mooney et al., 2012; Tracy et al., 2012; Schulz et al.,
331 2013; Metzner et al., 2015), but require elaborate data processing and are suitable for relatively
332 small and young root systems due to technical restrictions in container size (Bucksch et al., 2014;
333 Landl et al., 2018) and are scanned at low throughput (Downie et al., 2015; Landl et al., 2018).
334 Studies under controlled conditions enable study of growth of roots over time, however are
335 generally used to assess less complex root structures on younger plants from germination to ca. 10
336 day after germination (Clark et al., 2011). This is a particular limitation for monocot roots which
337 develop more axial roots over time. Destructive field sampling methods such as shovelomics
338 (Trachsel et al., 2011; Burrige et al., 2016) allow the measurement of the root crown phenotype
339 however is associated with loss and possible displacement of fine roots (Pagès and Pellerin, 1994;
340 Pellerin and Pagès, 1994). Estimates of phenotyping metrics such as fractal dimension is sensitive
341 to incompleteness of the excavated root network (Nielsen et al., 1999; Bucksch et al., 2014).

342 *SimRoot*, a functional-structural plant model has been used extensively for elucidating the
343 functional value of one or more phenes, and to analyze phene interactions and root complexity
344 (Walk et al., 2004; Walk et al., 2006; Lynch, 2007; Postma and Lynch, 2011a; Postma and Lynch,
345 2011b; Postma et al., 2014; Dathe et al., 2016; Rangarajan et al., 2018). Simulations with *SimRoot*
346 enable comparing genotypes that vary only in the phene of interest, i.e. near-isophenic lines, which
347 are exceedingly difficult to obtain empirically (Lynch, 2011; York et al., 2013; Rangarajan et al.,
348 2018). A significant advantage of using *SimRoot* is that root architecture over time is known in its
349 entirety devoid of measurement and sampling error. Highly complex root systems can be simulated
350 and resulting root images can be used without any requirement of cleaning images as there is no
351 image noise. Root image co-ordinates are recorded as they grow in 3D space, and so root
352 phenotyping traits can be measured at any time step for any number of time steps without
353 additional effort. One of the major hurdles in phenotyping roots is that artifacts may be present so
354 that the representation of the root system may not be accurate.

355 *4.2 Correlation among estimates of phenes and phene aggregates are an emergent property of* 356 *SimRoot*

357 Our studies with phenes and phene aggregates show that some phenes are highly correlated with
358 each other. *SimRoot* is a mechanistic model and has no fixed relationships for the root architectural
359 parameters. The phenotype is simulated based on a set of input parameters including number of
360 roots of different root classes, root growth angles, root diameter, lateral root branching density
361 with some stochasticity included in each of the parameters. Due to carbon feedbacks and restricted
362 carbon availability, not all phenotypes are simulated. The root system develops based on carbon
363 availability as determined by availability in the seed initially. Plant growth and development
364 occurs as emerging from underlying processes such as photosynthesis, allocation of assimilates,
365 uptake of nutrients and determine the growth of the plant root system (Walk et al., 2006; Postma
366 et al., 2014; Rangarajan et al., 2018). There are no correlations built into the model and the
367 correlations seen among the phenes in the phenotypes are a result of the mechanistic processes that
368 are captured in the model. For example, larger diameter root axes result in larger carbon sinks
369 leaving few resources for other roots. A set of carbon allocation rules determine carbon allocated
370 to different root classes with axial roots having precedence over lateral roots. This is seen as a
371 reduction in lateral root length when the number of roots is greater or when the root diameter is
372 greater. Growth rates of the root tips are a function of carbon availability and if severe carbon

373 limitations occur (as would occur if the phenotype being simulated had many axial roots, greater
374 branching density or large diameter roots or combination of these), axial root length is affected
375 and in extreme cases may inhibit the emergence of roots emerging later. Attempts to factorially
376 design phenotypes based on discrete values of the phenic states resulted in some phenotypes not
377 developing for more than few days due to carbon limitations. This is because *SimRoot* keeps track
378 of resource allocation (C, N, P) and trade-offs in carbon allocation result in trade-offs among root
379 traits, as occurs with real plants. The trade-offs include longer axial roots and longer lateral roots
380 when number of axial roots/axial root diameter is reduced, which are seen as high correlations
381 among those phenes. Only those phenotypes that supported plant growth for 40 days were used so
382 that the metrics were dependent only on the phenotype. All metrics were recalculated/extracted
383 from the simulated root system in order to get an accurate estimate of the phenotypic metric.

384 Correlations also exist among phene aggregates; *maximum depth* and *major ellipse axis* were
385 highly correlated; *Convex hull area*, *convex hull volume*, *maximum width* and *minor ellipse axis*
386 were also highly correlated as seen in several other studies *Major ellipse axis* and *maximum depth*
387 are measures of rooting depth (Wedger et al., 2019) and were correlated with primary root length.
388 *Maximum width*, *minor ellipse axis* and *convex hull* are phene aggregates which characterize
389 expansion in sense of the outer shape of the root system (Paulus et al., 2014). *Maximum width* and
390 *minor ellipse axis* estimates are one-dimensional metrics, *convex hull* is a function of all three
391 dimensions (Mairhofer et al., 2013). These differences mean that as the root grows, estimates of
392 the *convex hull* have a much greater increase in magnitude than does *maximum width*. *Solidity*,
393 which is a ratio of the *total volume and convex hull*, could increase or decrease as *total volume* is
394 dependent on number of roots, lengths of the roots of different root classes and diameters, however
395 *convex hull* estimates the volumetric expansion of the outer shape of the root system.

396 *4.3 Phene aggregate metrics are not an unique estimate of phenotype*

397 Phene aggregate measures such as rooting depth are functionally useful traits, as has been
398 demonstrated by several studies. Rooting depth however is influenced by several phenes including
399 root angle, number of roots, LRBD, as shown by several studies (e.g. Manschadi et al., 2010;
400 Trachsel et al., 2013; Saengwilai et al., 2014b; Zhan et al., 2015; Gao and Lynch, 2016). A measure
401 of rooting depth however does not provide any information on the constituent phenes such as
402 rooting angle, number of roots etc. which all contribute to rooting depth. The same is true for other
403 phene aggregate measures such as convex hull volume. Convex hull, defined as the shape of an
404 object created by joining its outermost points, has been used as an indicator of the extent of soil
405 exploration. Calculating convex hull from point clouds requires minimal preprocessing, making it
406 a popularly used phenotyping metric. Although convex hull can provide interesting information
407 about the overall root system shape (Ingram et al., 2012; Zurek et al., 2015), it was not found to
408 be useful in discriminating between phenotypes of different populations (Iyer-Pascuzzi et al.,
409 2010). In a study comparing roots in compacted and uncompacted soil where root geometry is
410 severely affected by soil characteristics, convex hull volume differed by a factor of 3 (Tracy et al.,
411 2012). Here we demonstrate that phenotypes with convex hull estimates within as low as 5% of
412 each other can have phenes expressed in distinctly different states.

413 While the estimate of a single phene aggregate metric might not be useful in discriminating
414 between phenotypes, using multiple phene aggregate metrics can probably be useful. Each phene
415 aggregate trait gives an estimate of the phenotype by capturing different combinations of phenes.
416 *Total length*, *area* and *volume* give an estimate of the size of the root system by indirectly
417 measuring the number of roots, length of roots and the diameter of the roots. *Convex hull*, *minor*

418 *ellipse axis, major ellipse axis, ellipse aspect ratio, maximum width and maximum depth* provide
419 information of the extent of the shape by providing a measurement root angle and root length.
420 Estimates of these phene aggregates, even though they distinguish features of the root system and
421 complement one another in important ways (Topp et al., 2013), do not provide any information on
422 the phene states that comprise the phenotype. Studies aimed at finding root traits which
423 discriminate between populations / phenotypes have found that no single phene aggregate trait was
424 important (Zurek et al., 2015). Which traits were key as well as the number of informative traits
425 were highly dependent on differences between RSA and the imaging day (Zurek et al., 2015).
426 Complexity of RSA over time reinforce the necessity of assessing a large number of traits to
427 distinguish between different varieties as well as individual varieties at different ages (Iyer-
428 Pascuzzi et al., 2010; Topp et al., 2013; Zurek et al., 2015). Accuracy of the different metrics is
429 strongly linked to the root phenotypes analyzed as well as their size and complexity.

430 *4.4 Variation in estimates from 2D projection images arise especially due to phenes that determine* 431 *the geometry of the root system*

432 Root angle is an important phene for soil resource capture; studies have shown that shallow root
433 angles are important for capture of immobile soil nutrients and deep root angles for mobile soil
434 nutrients as well as water capture (Zhu et al., 2005a; Omori and Mano, 2007; Uga et al., 2011;
435 Dathe et al., 2013; Lynch, 2013; Miguel et al., 2013; Miguel et al., 2015; Dathe et al., 2016; Lynch,
436 2019). Differences in root growth angle result in phenotypes with distinct differences due to trade-
437 offs in the capture of mobile and immobile soil resources and resulting trade-offs in phenes leading
438 to large effects in biomass production (Ge et al., 2000; Dathe et al., 2016; Rangarajan et al., 2018).
439 Our results show that estimate of root angle is affected by the 2D projection of the root system.
440 Root angle determines the geometry of the root system and was found to be an important variable
441 in determining variations in *convex hull area, convex hull volume, maximum width and minor*
442 *ellipse axis* (Table 2). Aggregate phene traits capturing the geometry or overall shape of the root
443 cannot be measured accurately using estimates derived from 2D data. The variation in the estimates
444 of root angle when measured using 2D projections affect the estimates of all phene aggregate traits
445 in which they play an important role directly or indirectly; these include secondary phene aggregate
446 traits such as solidity, ellipse aspect ratio as well as root complexity traits *FD* and *FA* (Figure 8
447 and Figure 9). Variation is greater in phene aggregates which are estimates of some function of
448 more than one aggregate phene. Even though our root phenotypes are simulated, they are based on
449 empirical parameters, and differences in number of roots, angles of each root class etc. were varied
450 and as a result, our root phenotypes were not symmetrical, to replicate actual root system in fields.
451 This is important because most roots found in nature are not symmetrical. We found that greater
452 asymmetry was associated with greater variation in the aggregate phenotypic metrics estimated
453 from 2D projections. Results from studies using 2D images from gel culture, growth pouches,
454 narrow growth containers with a transparent face, etc., should be interpreted with caution.

455 *4.5 Variation in phene aggregate metrics with time is species dependent*

456 We analyzed root phenotypes of two species, maize and common bean, representing a monocot
457 and a dicot root architecture. The main difference between bean, which is a dicot root system, and
458 monocot root systems is that new roots (laterals) emerge from already existing roots in dicots,
459 whereas in monocots nodal roots continually emerge over time from shoot nodes near or above
460 the soil surface (Rangarajan et al., 2018). Therefore, the vertical distribution of roots vary between
461 maize and bean, with the bean root system having a relatively equal root distribution whereas

462 maize has more proportion of roots in the topsoil (Postma and Lynch, 2012; Zhang et al., 2014).
463 The number of roots as well as root diameter depends on the nodal position in maize. This is
464 probably the reason for the great temporal variation in metrics such as volume distribution and
465 bushiness index which are related to root size. It has been suggested that metrics accurate for small
466 dicot root systems might fail for large dicot or small monocot root systems (Lobet et al., 2017).
467 Our study confirms that estimates of phene aggregates are not only dependent on phenotype and
468 time but also on the plant species.

469 *4.6 Metrics of root complexity*

470 Fractal parameters are different from all the estimated phene aggregates in that they do not provide
471 information on shape of the phenotype, extent of shape or size of the root system, but instead
472 measure the geometric complexity of the root phenotype (Fitter and Stickland, 1992; Nielsen et
473 al., 1997; Nielsen et al., 1999). All the phenes tested were important in determining fractal
474 estimates. Fractal dimension was useful in differentiating between P inefficient and P efficient
475 bean genotypes (Nielsen et al., 1999) as well study of roots fractal parameters with uptake of
476 diffusion limited nutrients and between genotypic variation in wheat, study developmental
477 responses in rice (Manschadi et al., 2008; Wang et al., 2009). It was found, however, that not a
478 single but combinations of multiple fractal measurements provide useful information (Nielsen et
479 al., 1999; Walk et al., 2004). Phenotypes with comparable aggregate phene trait estimates can be
480 a result of different combinations of phenes in distinctly different phene states. This implies that
481 estimates of phene aggregate traits measure the aggregate of multiple phenes (York et al., 2013).
482 Studies have shown that complex phenotypic traits such as root complexity as measured by fractal
483 analysis are determined by a multitude of genes with small effects (Grift et al., 2011). Even though
484 several studies have resulted in identification of QTLs for aggregate phene traits (Topp et al., 2013;
485 Atkinson et al., 2015; Zurek et al., 2015; Kenobi et al., 2017), only two genes directly controlling
486 RSA have been cloned (Uga et al., 2011; Wedger et al., 2019). Estimates of QTL locations or
487 effects *per se* do not give us direct biological information regarding the product or function of each
488 gene and the interactions among genes (Bernardo, 2008). Phenes are unique, meaning, are the
489 product of only one set of genes and processes at a specified scale of resolution (Lynch and Brown,
490 2012; Lynch, 2019) and so, phene selection is more genetically tractable than selection for traits
491 that aggregate multiple phenes, because axiomatically phenes are under simpler genetic control
492 than any combination of phenes (Lynch, 2019).

493 *4.7 Selection of phenotypes based on phenes are useful for breeding*

494 Several phenes have been studied and their functional utility has been established including
495 number of roots (crown roots in maize, basal roots in bean), root growth angle (shallow for
496 phosphorus uptake and deep rooting angle for nitrogen capture), lateral root branching density and
497 length for nitrate uptake (Zhu et al., 2005b; Lynch, 2013; Trachsel et al., 2013; Saengwilai et al.,
498 2014; Miguel et al., 2015; Zhan and Lynch, 2015; Rangarajan et al., 2018; Sun et al., 2018). In the
499 bean root system, basal roots emerge at the seedling stage and seedling root phenotypes have
500 significant relationships with mature root phenotypes in the bean root system. Number of basal
501 roots as well as basal root growth angle is stable over time as proven by the fact that studies
502 selecting for basal root number and angle at different stages of growth from seedling to few weeks
503 old plants (Liao et al., 2001; Vieira and Lynch, 2001; Vieira et al., 2008) have been consistent.
504 Genetic factors explained 52% to 57 % of genetic variation of phenes in bean including basal root
505 whorl number, basal root number, adventitious root number, and 52% of phenotypic variation in

506 taproot length in seedlings (Strock et al., 2019). Crown root and brace root number, angle and
507 LRBD were found to be genotype-specific and did not change across growth stages in maize
508 (Trachsel et al., 2013). Basal diameter remains constant in maize while apical diameter varies; in
509 dicots like bean, diameter increases with age due to secondary root growth (Strock et al., 2018).
510 Root growth/ elongation rates determine the length of the root and are thought to be phenes (York
511 et al., 2013; Strock et al., 2019). However, carbon limitations could result in delay of emergence
512 of axial roots as well as play a role in determining the final number of axial roots. Demotes-
513 Mainard and Pellerin (1992) have observed on maize that the emergence of axial roots was
514 delayed, and the final number of axial roots was reduced, with increasing levels of competition for
515 light between plants. Time of emergence of roots could also be an important phene, especially in
516 maize where roots emerge from different nodes over time. Recent studies have shown that cellular
517 anatomy varies among nodes providing evidence for node-specific traits (Yang et al, 2019). Our
518 approach using elemental phenes to discriminate between architecturally and anatomically distinct
519 phenotypes based on phene states has been used successfully for selection of functionally superior
520 phenotypes for different crop species (Burrige et al., 2017). We suggest that it is best to study the
521 phenotypes at their elementary level of organization, namely phenes in order to get a better
522 understanding of their functional value in terms of the interactions among the phenes and also to
523 identify their genetic features.

524 **Conclusions**

525 These results demonstrate that phenes including number of roots, diameter of roots, lateral root
526 branching density and root growth angle provide reliable descriptors of root phenotypes. Phenens
527 are also stable over time and independent of time of phenotyping. Estimates of phenens provide a
528 complete description of the resulting phenotype and also enable easier prediction of functional
529 attributes the phenotype could potentially have. Data from our *in-silico* phenotyping environment
530 provides access to complete information concerning root architectural phenotypes without
531 measurement error, sampling limitations, or confounding factors such as phenotypic plasticity or
532 root loss. Even under these conditions, estimates of aggregate phenotypic metrics are less reliable
533 than those of phene states. Even though the estimates of aggregate phenotypic metrics are
534 dependent on the phenotype, the estimates are not unique estimates of underlying states of the
535 constituent phenens. Estimates of phene aggregates also vary in magnitude at different time points
536 of growth, the magnitude of change being dependent on the aggregate phenotype metric used as
537 well as the constituent phenens. Unlike methods used to estimate aggregate phenotypes, estimation
538 of phenens involves simple, straightforward procedures and yield reliable results. We suggest that
539 measurement of phenens provides data that are more robust, reliable and relevant than metrics that
540 estimate the aggregation of multiple subtending phene states. We show this in the context of root
541 architectural phenotypes but propose that these concepts apply to phenomic analysis of any
542 organism.

543 **Acknowledgements**

544 HR designed and conducted the research, developed the analytical framework, analyzed the
545 results, and wrote the manuscript. JPL conceived and supervised the project and assisted with
546 experimental design, data interpretation and manuscript preparation. This research was supported
547 by the National Institute of Food and Agriculture, U.S Department of Agriculture Hatch project
548 4732 and the Foundation for Food and Agriculture Research 'Crops in Silico' project. The authors
549 declare that there is no conflict of interest regarding the publication of this article. Data generated
550 in this study is freely available from the corresponding author. The executable code of the version

551 of *SimRoot* employed in this study, parameters used to generate these data, and the raw data, are
552 all available at <https://figshare.com/s/58c7599752bcb75fbd76>.

553

554 **Figure Legends**

555 Figure 1: Representation of 2D projection of 3D root system (a) Visualization of maximum width,
556 major ellipse axis (b) and convex hull volume (c) of a 3D root system.

557 Figure 2: Cluster heatmap of phenotypic traits. Hierarchical clustering of a few phenotypes was
558 generated using Spearman correlation of max-min scaled phen values of bean phenotypes at 40
559 days (a). The color scale indicates the magnitude of the trait values (blue, low value; red, high
560 value). The numbers indicated on the heatmap refer to the phenotype in the specific row of the
561 heatmap. The corresponding phenotypes are visualized in (b). Primary roots are in black; basal
562 roots are in red; hypocotyl-borne roots are in green. # - number of axial roots; Axial.Diam – axial
563 root diameter; LRBD – lateral root branching density; Lat.Length – lateral root length; Lat.Diam
564 – lateral root diameter; BW1 – basal roots at whorl 1; BW2 – basal roots at whorl 2; BW3 – basal
565 roots at whorl 3; BW4 – basal roots at whorl 4; BW5 – basal roots at whorl 5; HBR – hypocotyl-
566 borne roots; PR – primary root.

567 Figure 3: Cluster heatmap of phenotypic traits. Hierarchical clustering of a few phenotypes was
568 generated using Spearman correlation of max-min scaled phen values of maize phenotypes at 40
569 days (a). The color scale indicates the magnitude of the trait values (blue, low value; red, high
570 value). The numbers indicated on the heatmap refer to a phenotype in the specific row of the
571 heatmap. The corresponding phenotypes are visualized in (b). Primary roots are in black; seminal
572 roots are in red; nodal roots are in green. # - number of axial roots; Axial.Diam – axial root
573 diameter; LRBD – lateral root branching density; Lat.Length – lateral root length; Lat.Diam –
574 lateral root diameter; NR1 – nodal roots at position 1; NR2 – nodal roots at position 2; NR3 –
575 nodal roots at position 3; NR4 – nodal roots at position 4; SR – seminal roots; PR – primary root.

576 Figure 4: Phenotypic trait relationship. Correlation matrix of phenes and phene aggregates
577 evaluated for bean root phenotypes (a). Correlation matrix of phenes and phene aggregates
578 evaluated for maize root phenotypes (b). The color scale indicates Spearman correlation coefficient
579 between traits (red, negative; blue, positive). Color intensity and size of the circle are proportional
580 to the correlation coefficients between two traits. Correlations between phenes are indicated by the
581 points in the red box, the green box contains the correlations between phene aggregates. BR –
582 basal roots; HBR – hypocotyl-borne roots; PR – primary root; SR – seminal roots; NR – nodal
583 roots; # - number of axial roots; Diam – axial root diameter; LRBD – lateral root branching density;
584 Axial Length – axial root length; Lat Length – lateral root length; Lat Diam – lateral root diameter.

585 Figure 5: Phene values of maize root phenotypes with comparable FD (a) and convex hull volume
586 (b). The heatmap shows values of the traits obtained by dividing the values with maximum value
587 of respective traits. The visualization of the phenotypes with similar FD and similar convex hull
588 volume are presented in (c) and (d) respectively. Phenotypes a1-a8 have similar FD; Phenotypes
589 b1-b8 have similar convexhull volume; PR -primary root; SR- seminal root; NR- nodal root;
590 LRBD – lateral root branching density; Len – axial root length; Lat.Len – lateral root length; # -
591 number of axial roots; FD – Fractal Dimension.

592 Figure 6: Convex hull volume, FD and total volume of bean root phenotypes with (a) one whorl
593 and shallow angle, (b) one whorl and deep angle(c) two whorls and fanned angle (d) four whorls
594 and fanned angles. The corresponding phenotypes are visualized in lower panel. FD – fractal
595 dimension.

596 Figure 7: Variation in phene and phene aggregate metrics estimated from rotational series of 2D
597 projected images of 3D bean root system (a) and 3D maize root system (b). BW -basal root; HBR-
598 hypocotyl-borne root; PR- primary root; SR – seminal root; NR -nodal root; # - number of roots;
599 Axial.Diam – axial root diameter; Axial.Length – axial root length; LRBD – lateral root branching
600 density; Lat.Length – lateral root length; FD – fractal dimension; FA – fractal abundance

601 Figure 8: Trait dynamics of bean root phenotypes over 30 days of growth from day 10 to day 40.
602 Change in estimates of phenes associated with basal whorl 3 (BW3) are shown in Figure 8(a).
603 Similar trends were seen in other root classes (Supplementary Figure S4(a)). Change in estimates
604 of the phene aggregates bushiness index, convexhull volume and fractal dimension (FD) are shown
605 in Figure 8(b). Trends in estimates of other phene aggregates included in this study are shown in
606 Supplementary Figure S4(b). The phenotypes for which the metrics are presented in Figure 8(a)
607 and (b) are visualized in Figure 8(c). Primary roots are in black; basal root in red; hypocotyl-borne
608 roots in green. BW3 – basal roots at whorl 3; Dia – axial root diameter; LRBD – lateral root
609 branching density; Lat.Len – lateral root length; # - number of axial roots.

610 Figure 9: Trait dynamics of maize root phenotypes over 30 days of growth from day 10 to day 40.
611 Change in estimates of phenes associated with seminal roots (SR) are shown in figure 9(a). Similar
612 trends were seen in other root classes (Supplementary Figure S5(a)). Change in estimates of the
613 phene aggregates bushiness index, convexhull volume and fractal dimension (FD) are shown in
614 Figure 9(b). Trends in estimates of other phene aggregates included in this study are shown in
615 Supplementary Figure S5(b). The phenotypes for which the metrics are presented in Figure 9(a)
616 and (b) are visualized in Figure 9(c). Primary roots are in black; seminal roots in red; nodal roots
617 in green. SR – seminal roots; Dia – axial root diameter; LRBD – lateral root branching density;
618 Lat.Len – lateral root length; # - number of axial roots.

619

620

621 Table 1: Aggregate phenic metrics, definition and method of obtaining them from *SimRoot* output

622

Parameter	3D	2D	Description	Measurement
Total Length	Y	Y	Summed length along the whole root system	Calculated from <i>SimRoot</i> output
Total Area	Y	Y	Summed surface area of the whole root system	Calculated from <i>SimRoot</i> output
Total Volume	Y	Y	Summed volume of the whole root system	Calculated from <i>SimRoot</i> output
Maximum width	Y	Y	Maximum horizontal width of the whole root system	Calculated using minimum enclosing circle algorithm in R
Maximum depth	Y	Y	Maximum vertical depth of the whole root system	Calculated from <i>SimRoot</i> output
Median no. of roots	Y	Y	Median no. of roots from root counts	Calculated from <i>SimRoot</i> output
Maximum no. of roots	Y	Y	No. of roots at the 84th percentile of a sorted list (smallest to largest) of root counts	Calculated from <i>SimRoot</i> output
Bushiness	Y	Y	Ratio of the maximum no. of roots to the median no. of roots	Calculated from <i>SimRoot</i> output
Volume distribution	Y	Y	Ratio of the volume of the root system contained above one-third depth of the root system to the volume of the root system contained below one-third depth of the root system	Calculated from <i>SimRoot</i> output
Convex hull volume	Y	Y	Volume of the convex hull that encompasses the whole root system	Obtained using <code>ConvHulln</code> function in R
Convex hull area	Y	Y	Surface Area of the convex hull that encompasses the whole root system	Obtained using <code>ConvHulln</code> function in R
Solidity	Y	Y	Ratio of volume to convex hull volume	Calculated
Major Ellipse axes	Y	N	Length of major axis of an ellipse best fit to overall shape and size of root system	Obtained using minimum volume enclosing ellipse algorithm in R
Minor Ellipse Axes	Y	N	Length of minor axis of an ellipse best fit to overall shape and size of root system	Obtained using minimum volume enclosing ellipse algorithm in R
Ellipse axis aspect ratio	Y	N	Ratio of major axis of ellipse to minor axis	Calculated from minor ellipse axes and major ellipse axes
Fractal Dimension (FD)	Y	Y	Measure of root complexity. Fractal dimension expresses the space filling properties of a structure (e.g. root system) and is associated with branching pattern	Obtained using box count code written in R
Fractal Abundance (FA)	Y	Y	Measure of root complexity. Fractal abundance is associated with the volume of space explored	Obtained using box count code written in R

623

624 Table 2: Results of regression models created with random forest. The R^2 values of Random
 625 Forest model with entire set of variables and those with only most important variables are
 626 presented for the bean and maize aggregate phenetic metrics.

Aggregate Phenotypic Metric	R^2 (% Variance Explained)			
	Bean		Maize	
	Model With All Variables	Model with Most Important Variables	Model with All Variables	Model with Most Important Variables
Total Length	89.5	91.6	82	85
Total Area	87	87	78	81
Total Volume	81.7	88.5	79	81.6
Volume Distribution	87	91	61	66
Max no. of roots	78.8	84	67	72.8
Median no. of roots	79.9	87	71	75
Bushiness	62	67	36	41
Max Depth	98.6	99.6	79	84
Max Width	91	90	95	99
Convex hull Area	97.8	97	90	93.4
Convex hull Volume	97.6	97.6	87	89.9
Ellipse Minor Axis	94.9	93.6	80	85
Ellipse Major Axis	96.7	97.3	95	98.6
Ellipse Aspect Ratio	85.9	87.4	51.9	62
Solidity	97.4	97.5	89	89
FD	67	68	16	20
FA	93.5	94.9	88	90

627

628 Note: Random Forest possesses its own reliable statistical characteristics, which could be used for
 629 validation and model selection. The major criterion for estimation of internal predictive ability of
 630 the Random Forest models and model selection is the value of R^2 . R^2 in Random Forest is
 631 interpreted as a measure of predictive quality of Random Forest model on independent samples.
 632 Random Forest models were run with the aggregate phenotype as dependent variable and all the
 633 phenes as predictor variables. Most important variables were chosen based on the % increase in
 634 mean square and Random Forest models were run with only the most important variables.

635

636 Table 3: Summary of the most important variables selected by random forest model for each
 637 phenotyping metric evaluated for bean root system and maize root system

638

Phene aggregates	Phenes						
	Axial Length	Root	No. of Roots	LRBD	Angle	Diameter	Lateral Root Length
Total Length	Maize Bean		Maize Bean	Maize Bean			Maize Bean
Total Area	Maize Bean		Maize	Maize Bean		Bean	Maize Bean
Total Volume	Maize Bean		Maize Bean	Maize Bean		Maize Bean	Maize Bean
Volume Distribution	Maize Bean		Maize Bean	Maize		Maize Bean	Maize Bean
Max # of Roots	Maize Bean		Maize	Maize Bean			Maize Bean
Median # of Roots	Maize Bean		Maize	Maize Bean			Maize Bean
Bushiness	Maize Bean		Maize	Maize Bean	Bean	Maize	Maize Bean
Max Depth	Maize Bean				Maize	Maize Bean	Maize Bean
Max Width	Maize Bean				Maize Bean		Maize Bean
Convex hull Area	Maize Bean				Maize Bean		Maize Bean
Convex hull Volume	Maize Bean				Maize Bean		Maize Bean
Ellipse Minor Axis	Maize Bean				Maize Bean		Maize Bean
Ellipse Major Axis	Maize Bean						Maize Bean
Ellipse Aspect Ratio	Maize Bean		Maize Bean	Bean	Maize Bean	Bean	Maize Bean
Solidity	Maize Bean		Maize		Maize Bean	Maize Bean	Maize Bean
FD	Maize Bean		Maize Bean	Maize Bean	Maize Bean	Maize Bean	Maize Bean
FA	Maize Bean		Maize	Maize Bean	Bean		Maize Bean

639

640

641 **Citations**

642

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834 **Supplementary Materials**

835

836 Supplementary 1.

837 Supplementary Figure S1: Representative images of 2D projections of a maize roots system
838 rotated by 20°, 60°, 100°, 140°, 180°, 220°, 260°, 300°, 340°.

839 Supplementary Figure S2: Cluster heatmap of phenotypic traits. Hierarchical clustering of all bean
840 phenotypes was generated using Spearman correlation coefficient of min-max scaled phenic
841 values at 40 days (a). The color scale indicates the magnitude of the trait values (blue, low
842 value ; red, high value). The numbers indicated on the heatmap refer to a representative
843 phenotype in the specific region of the heatmap. The corresponding phenotypes are visualized
844 in (b). # - number of axial roots; Axial.Diam – axial root diameter; LRBD – lateral root
845 branching density; Axial.Length – axial root length; Lat.Length – lateral root length;
846 Lat.Diam – lateral root diameter; BW1 – basal roots at whorl 1; BW2 – basal roots at whorl
847 2; BW3 – basal roots at whorl 3; BW4 – basal roots; BW5 – basal roots at whorl 5; HBR -
848 hypocotyl-borne roots; PR – primary roots.

849 Supplementary Figure S3: Cluster heatmap of phenotypic traits. Hierarchical clustering of all
850 maize phenotypes was generated using Spearman correlation coefficient of min-max scaled
851 phenic values of at 40 days (a). The color scale indicates the magnitude of the trait values
852 (blue, low value ; red, high value). The numbers indicated on the heatmap refer to a
853 representative phenotype in the specific region of the heatmap. The corresponding
854 phenotypes are visualized in (b). # - number of axial roots; Axial.Diam – axial root diameter;
855 LRBD – lateral root branching density; Axial.Length – axial root length; Lat.Length – lateral
856 root length; Lat.Diam – lateral root diameter; NR1 – nodal roots at position 1; NR2- nodal
857 roots at position 2; NR3 – nodal roots at position 3; NR4 – nodal roots at position 4; SR –
858 seminal roots; PR – primary roots.

859 Supplementary Figure S4: Trait dynamics of bean root phenotypes over 30 days of growth from
860 day 10 to 40. Change in estimates of phenes (a). Change in estimates of phenic aggregates (b).
861 BW1 – basal roots at whorl 1; BW2 – basal roots at whorl 2; BW4 – basal roots at whorl 4;
862 BW5 – basal roots at whorl 5; HBR – hypocotyl-borne roots; PR – primary root; Dia – axial
863 root diameter; LRBD – lateral root branching density; Lat.Len – lateral root length; # -
864 number of axial roots; FA – fractal abundance.

865 Supplementary Figure S5: Trait dynamics of maize root phenotypes over 30 days of growth from
866 day 10 to 40. Change in estimates of phenes (a). Change in estimates of phenic aggregates (b).
867 NR1 – nodal roots at position 1; NR2 – nodal roots at position 2; NR3 – nodal roots at position
868 3; NR4 – nodal roots at position 4; PR – primary root; Dia – axial root diameter; LRBD –
869 lateral root branching density; Lat.Len – lateral root length; # - number of axial roots; FA –
870 fractal abundance.

871 Supplementary 2.

872 Supplementary Table S1: Range of input values for generating bean root phenotypes. PR – primary
873 root; HBR- Hypocotyl-Borne-Root; BW – Basal Whorl; BW1, BW2, BW3, BW4, BW5 refer
874 to the position of the basal whorl counted from basipetal to acropetal position; Dia – axial
875 root diameter; Lat.Dia – lateral root diameter; LRBD – lateral root branching density.

876 Supplementary Table S2: Range of input values for generating maize root phenotypes. PR -
877 Primary Root; SR -Seminal Root; NR-Nodal Root; NR1, NR2, NR3, NR4 refer to the nodal
878 root position; Dia – axial root diameter; Lat.Dia – lateral root diameter; LRBD – lateral root
879 branching density. *NR at different positions were considered to have similar parameters.

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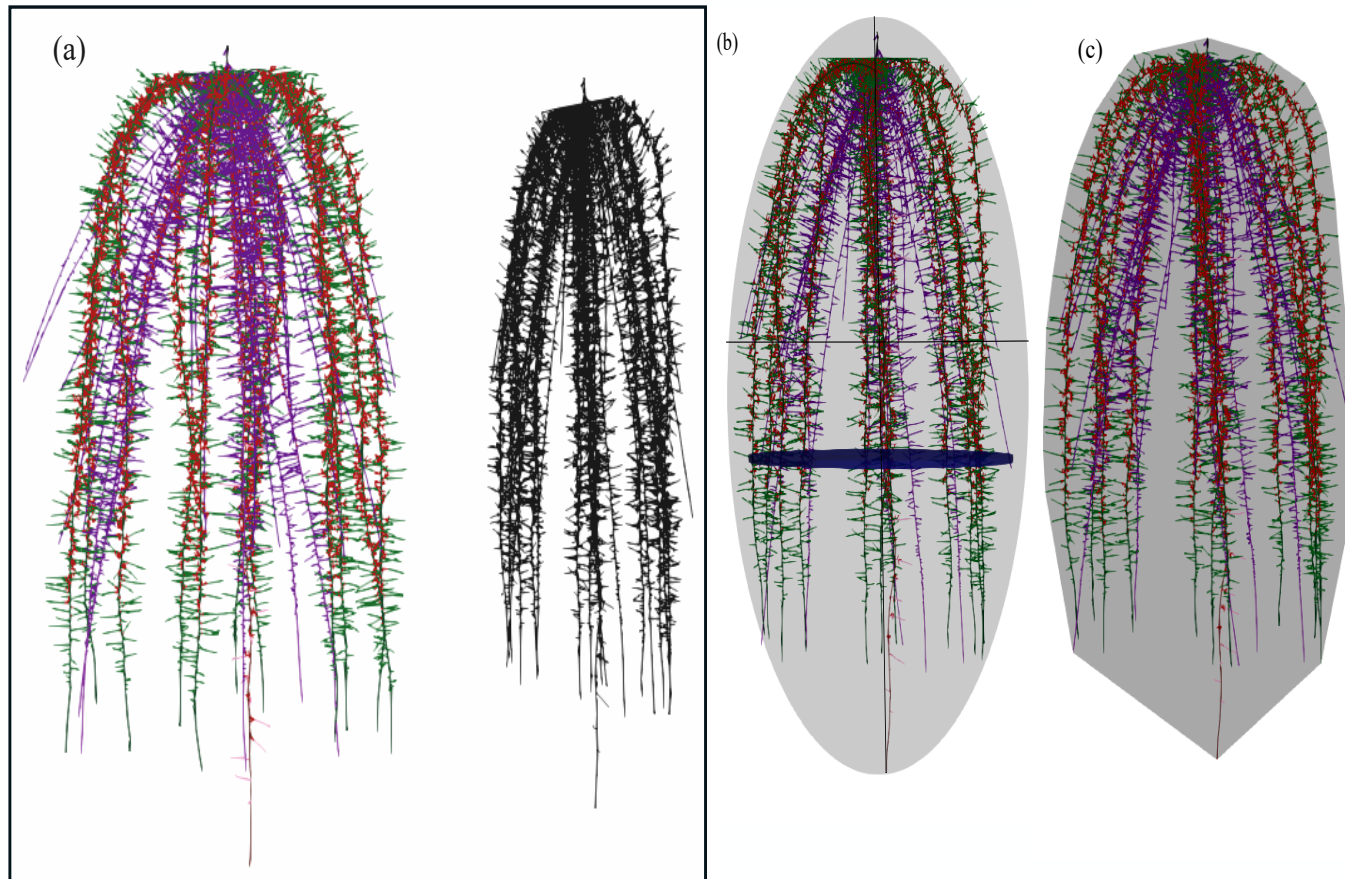
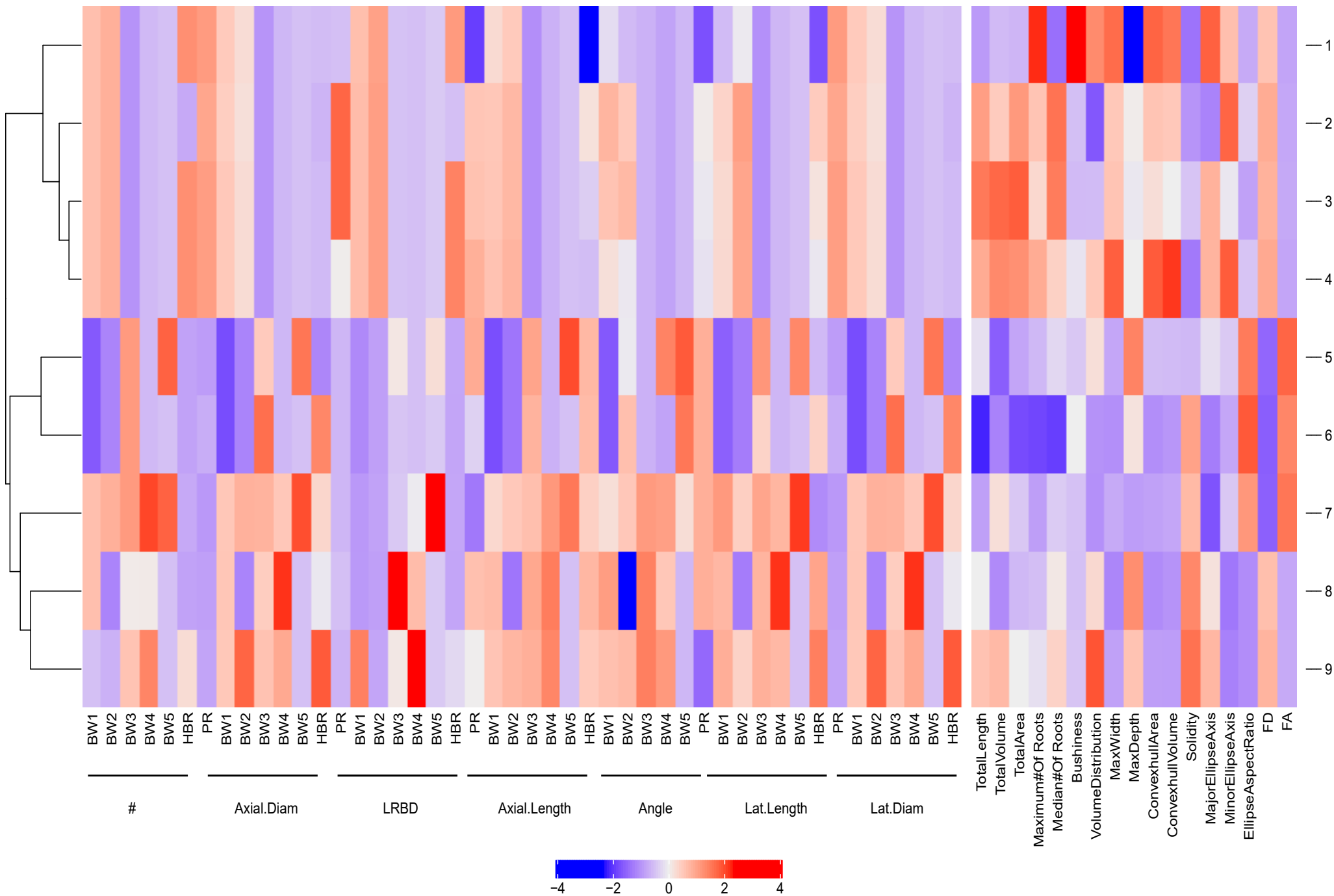


Figure 1 : Representation of 2D projection of 3D root system (a) Visualization of maximum width, ellipse major and minor axis (b) Convex hull volume of a 3D root system.

Phene

Phene Aggregate



(a)

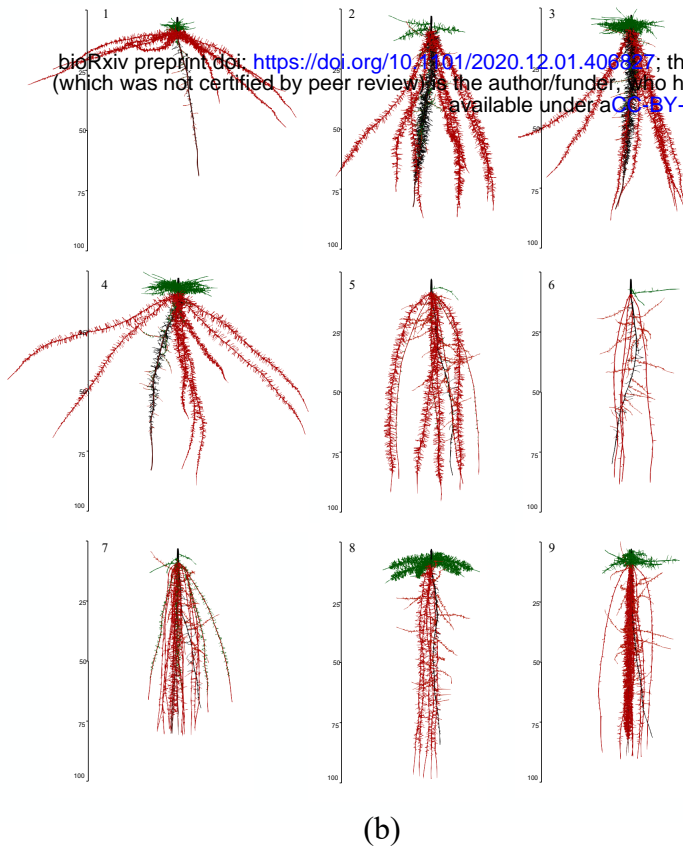
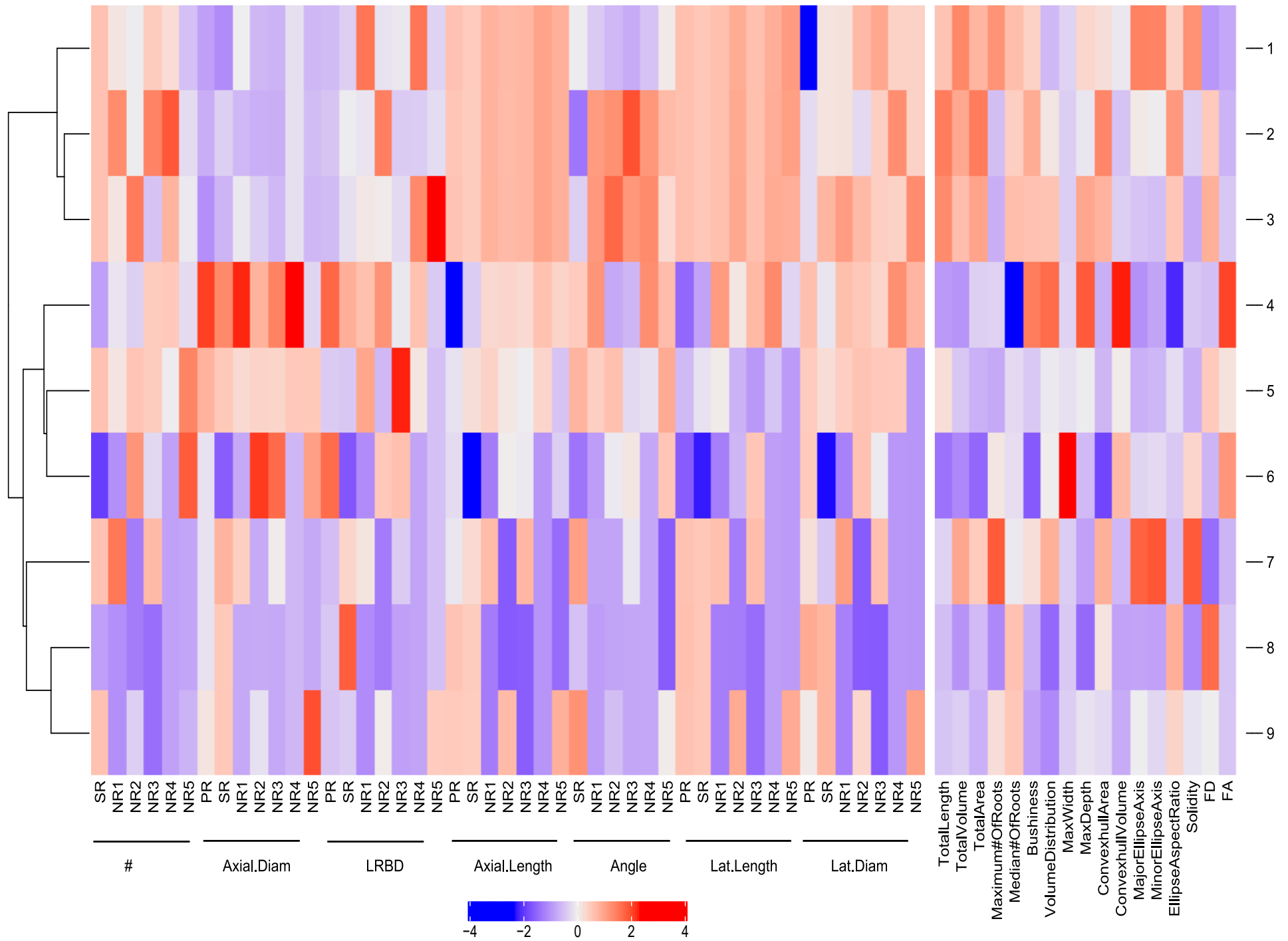


Figure 2: Cluster heatmap of phenotypic traits. Hierarchical clustering of a few phenotypes was generated using Spearman correlation coefficient of max-min scaled phen values of bean phenotypes at 40 days (a). The color scale indicates the magnitude of the trait values (blue, low value; red, high value). The numbers indicated on the heatmap refer to a phenotype in the specific row of the heatmap. The corresponding phenotypes are visualized in (b). Primary roots are in black; basal roots are in red; hypocotyl-borne roots are in green. # - number of axial roots; Axial.Diam - axial root diameter; LRBD - lateral root branching density; Lat.Length - lateral root length; Lat.Diam - lateral root diameter. BW1 - basal roots at whorl 1; BW2 - basal roots at whorl 2; BW3 - basal roots at whorl 3; BW4 - basal roots at whorl 4; BW5 - basal roots at whorl 5; HBR - hypocotyl-borne roots.

Phene

Phene Aggregate



(a)

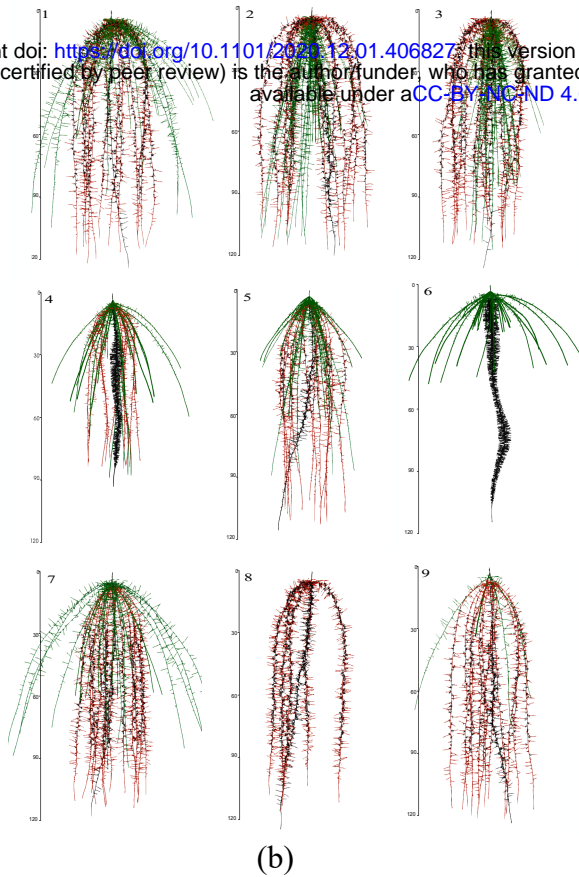
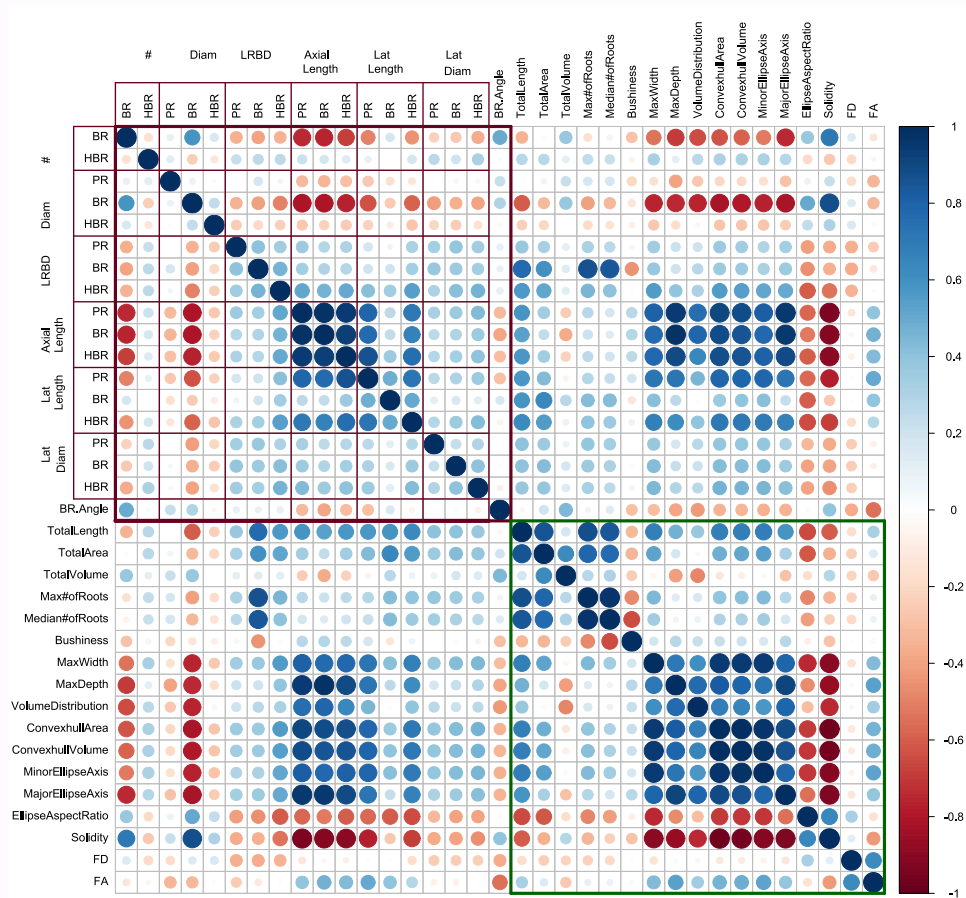
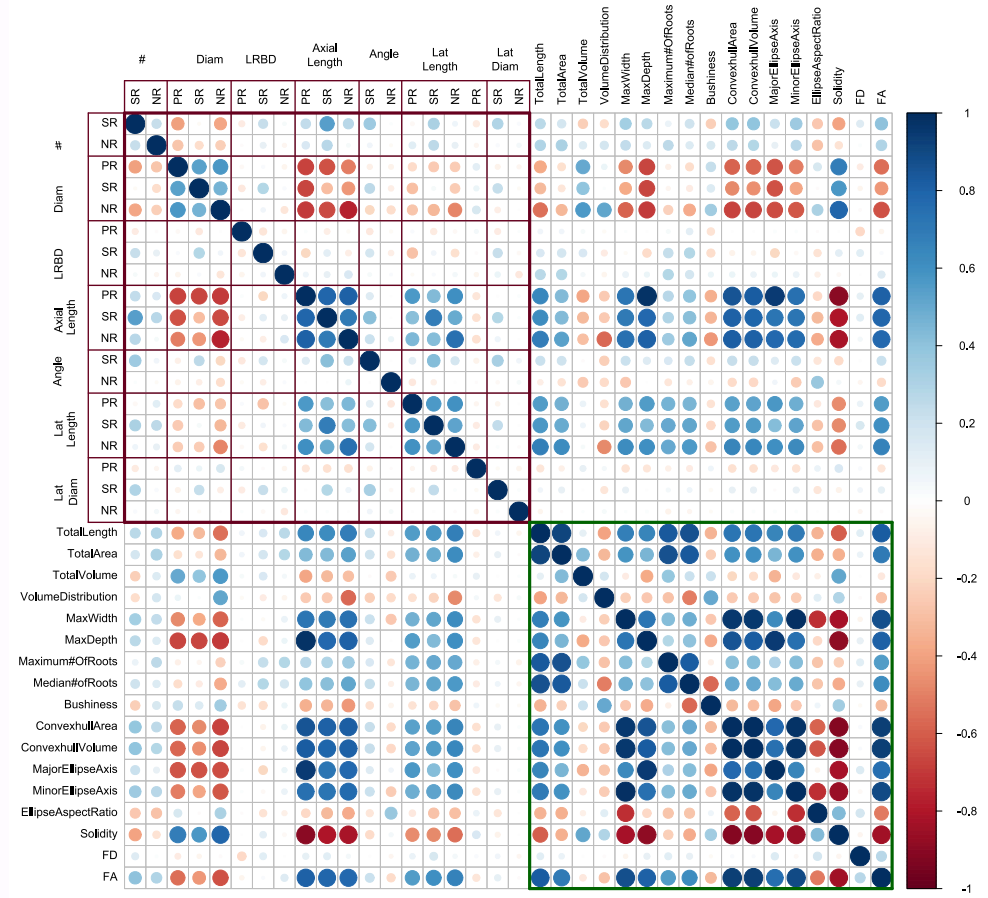


Figure 3: Cluster heatmap of phenotypic traits. Hierarchical clustering of a few phenotypes was generated using Spearman correlation coefficient of max-min scaled phen values of maize phenotypes at 40 days (a). The color scale indicates the magnitude of the trait values (blue, low value; red, high value). The numbers indicated on the heatmap refer to the phenotype in the specific row of the heatmap. The corresponding phenotypes are visualized in (b). Primary roots are in black; seminal roots are in red; nodal roots are in green. # - Number of roots; Axial.Diam - axial root diameter; LRBD - lateral root branching density; Axial.Length - axial root length; Lat.Length- lateral root length; Lat.Diam - lateral root diameter. NR1 - nodal roots at position 1; NR2 - nodal roots at position 2; NR3 - nodal roots at position 3; NR4 - nodal roots at position 4; SR - seminal roots; PR - primary root.



(a)



(b)

Figure 4: Phenotypic trait relationship. Correlation matrix of phenes and phene aggregates evaluated for bean root phenotypes (a). Correlation matrix of phenes and phene aggregates evaluated for maize root phenotypes (b). The color scale indicates Spearman correlation coefficients between two traits. Color intensity and size of the circle are proportional to the correlation coefficients between the two traits. Correlations between phenes are indicated by the points in the red box, the green box contains the correlations between phene aggregates. BR - basal roots; HBR - hypocotyl-borne roots; PR - primary root; SR - seminal roots; NR - nodal roots; # - number of axial roots; Diam - axial root diameter; LRBD - lateral root branching density; Axial Length - axial root length; Lat Length - lateral root length; Lat Diam - lateral root diameter; FD - fractal dimension; FA - fractal abundance.

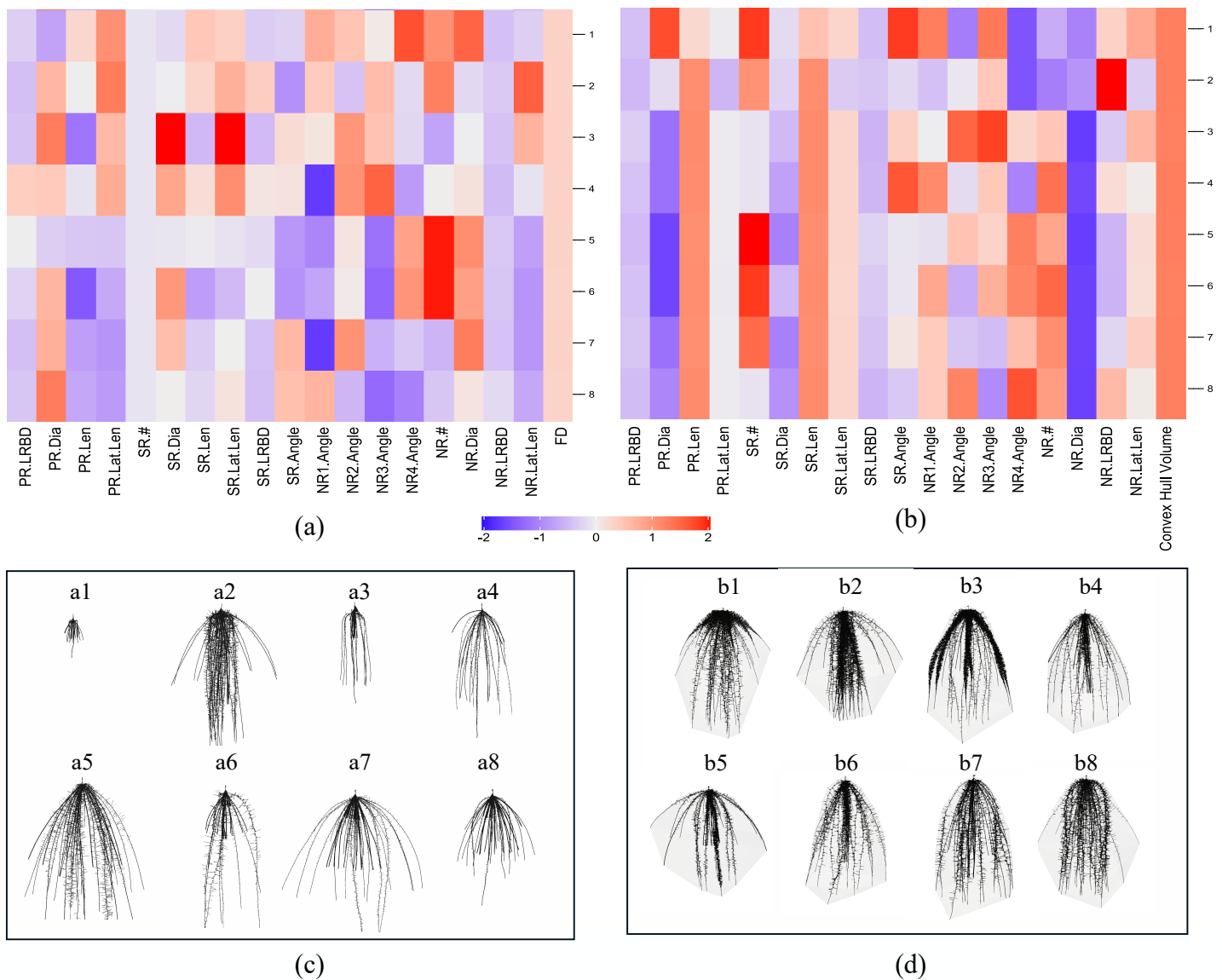


Figure 5: Phene values of maize root phenotypes with comparable FD (a) and convex hull volume (b). The heatmap shows values of the traits obtained by dividing the values with maximum values of respective traits. Phenotypes with similar FD and similar convex hull volume are visualized in (c) and (d) respectively. Phenotypes a1 - a8 have similar FD; Phenotypes b1-b8 have similar convex hull volume; PR - Primary Root; SR - Seminal root; NR - Nodal root; LRBD - lateral root branching density; Len - axial root length; Lat.Len - lateral root length; # - number of axial roots; Dia - diameter; FD - Fractal Dimension.

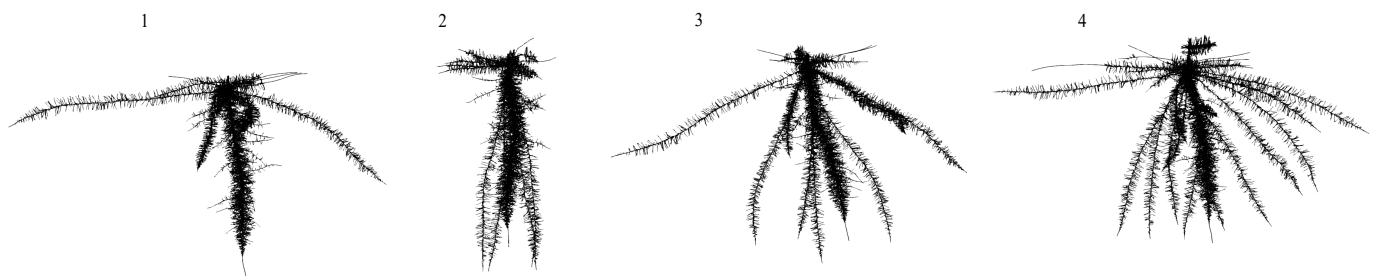
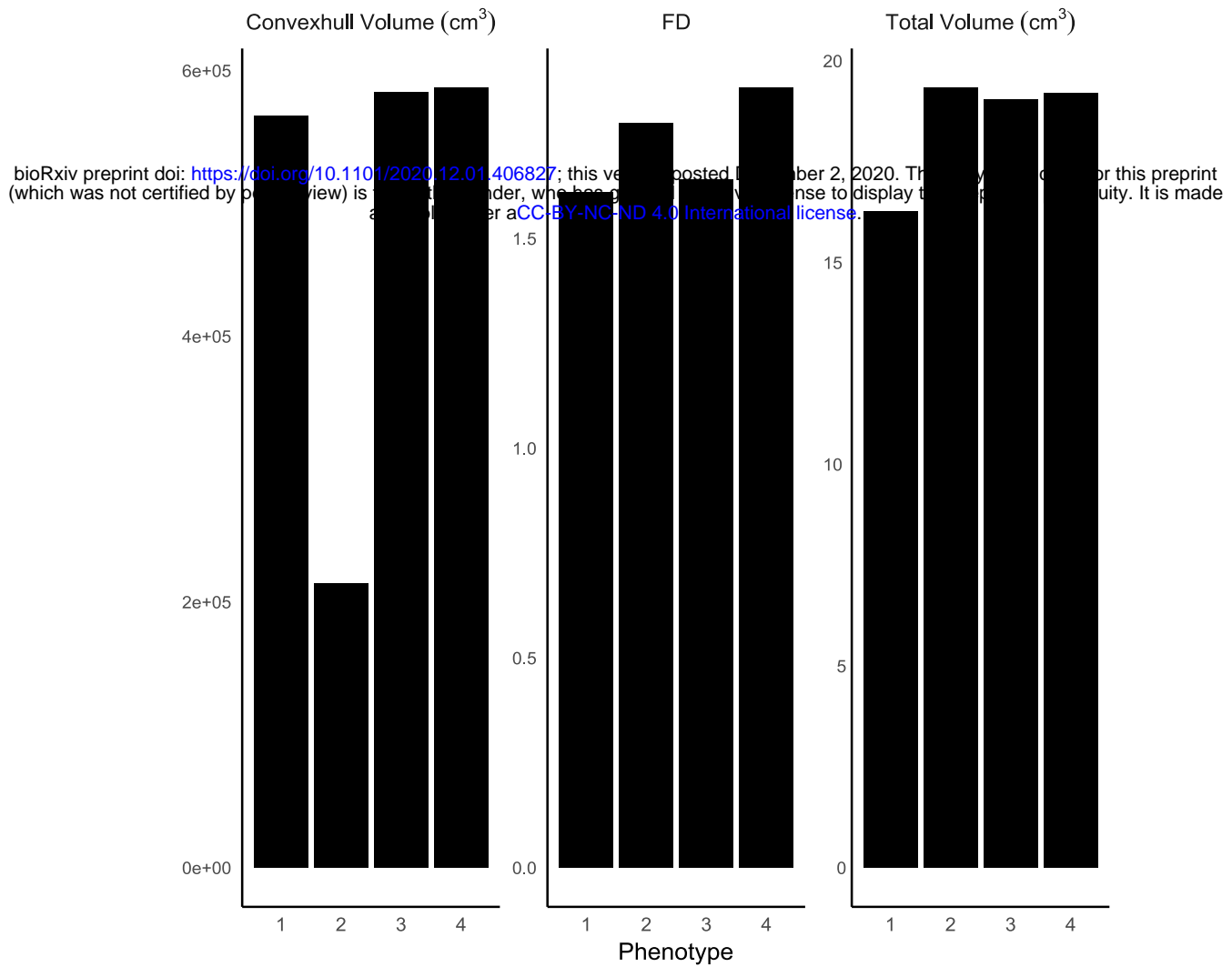
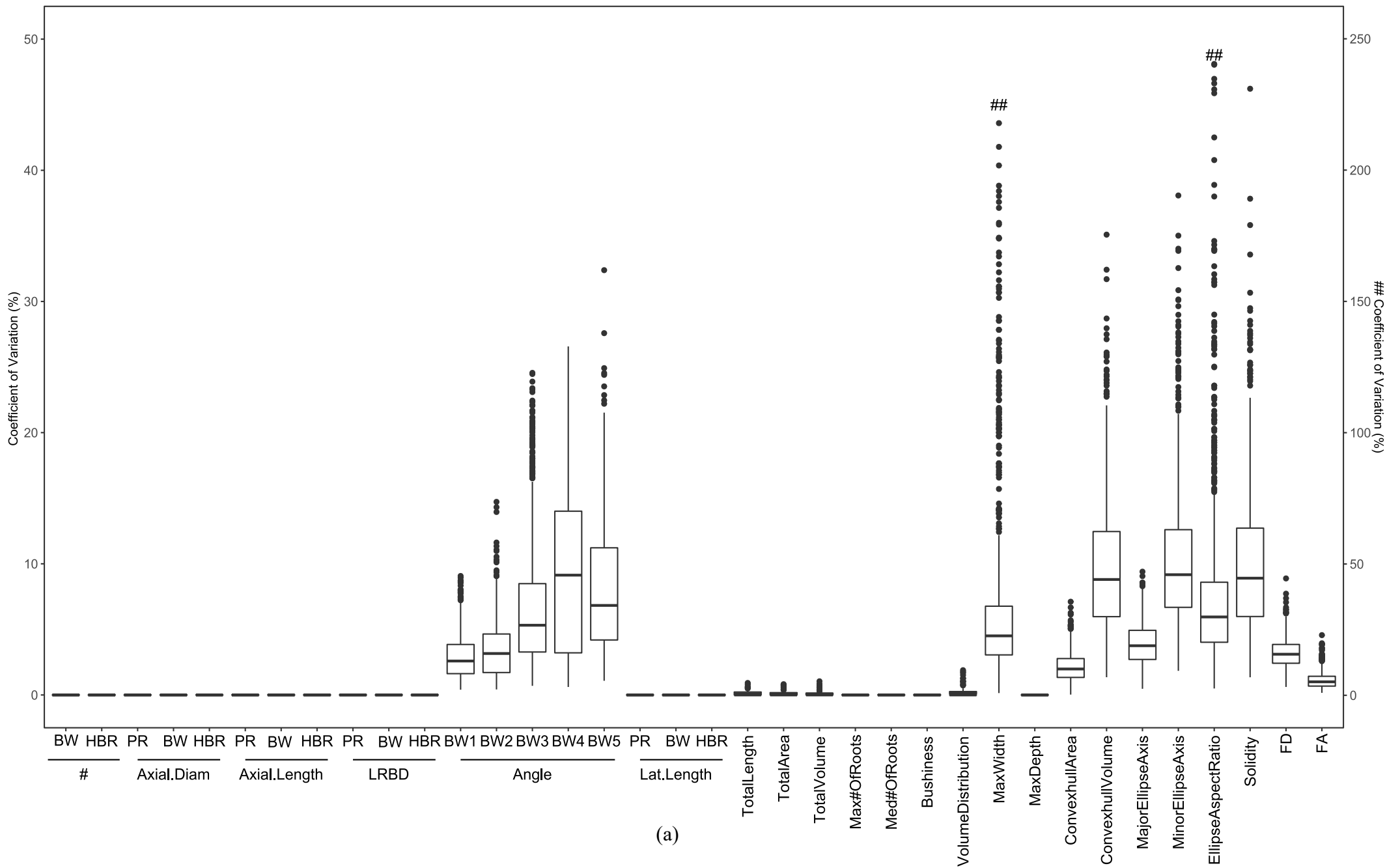


Figure 6: Convex hull volume, FD and total volume of bean root phenotypes with (1) one whorl and shallow angle (2) one whorl and deep angle (3) two whorls and fanned angles (4) four whorls and fanned angles. The corresponding phenotypes are visualized in lower panel. FD- Fractal dimension.



(a)

Coefficient of Variation (%)

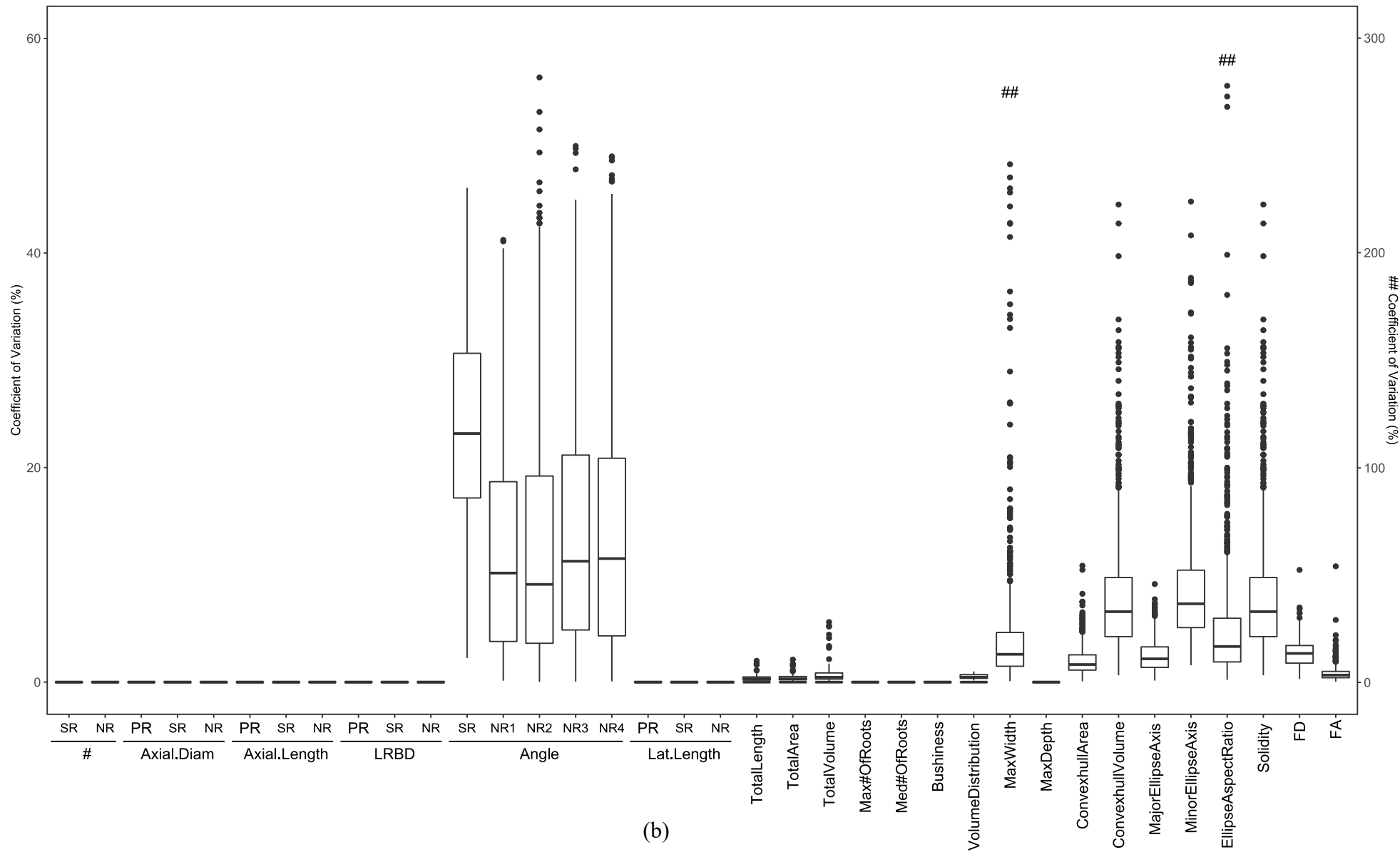
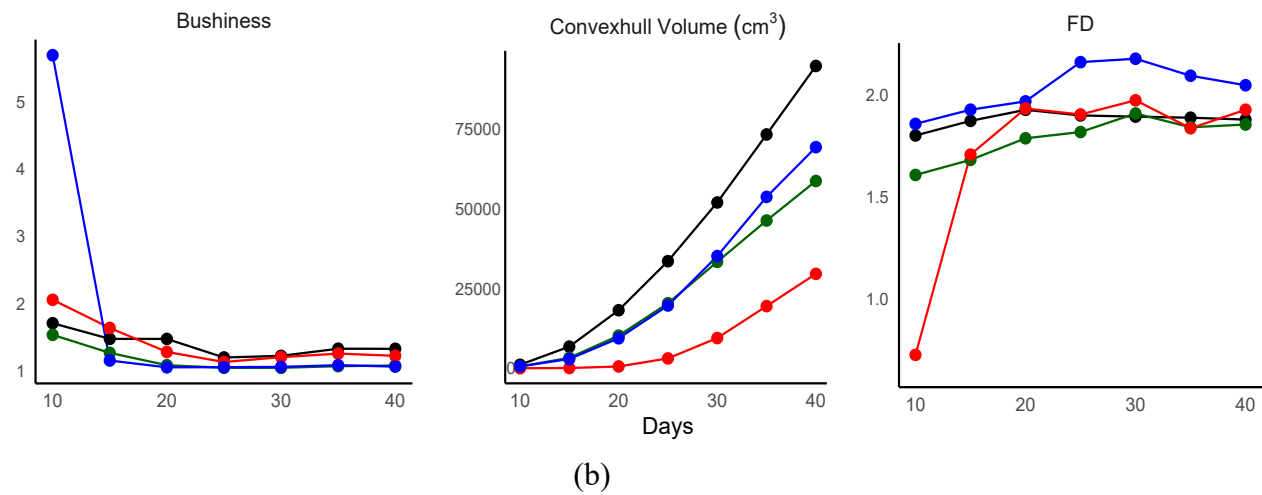
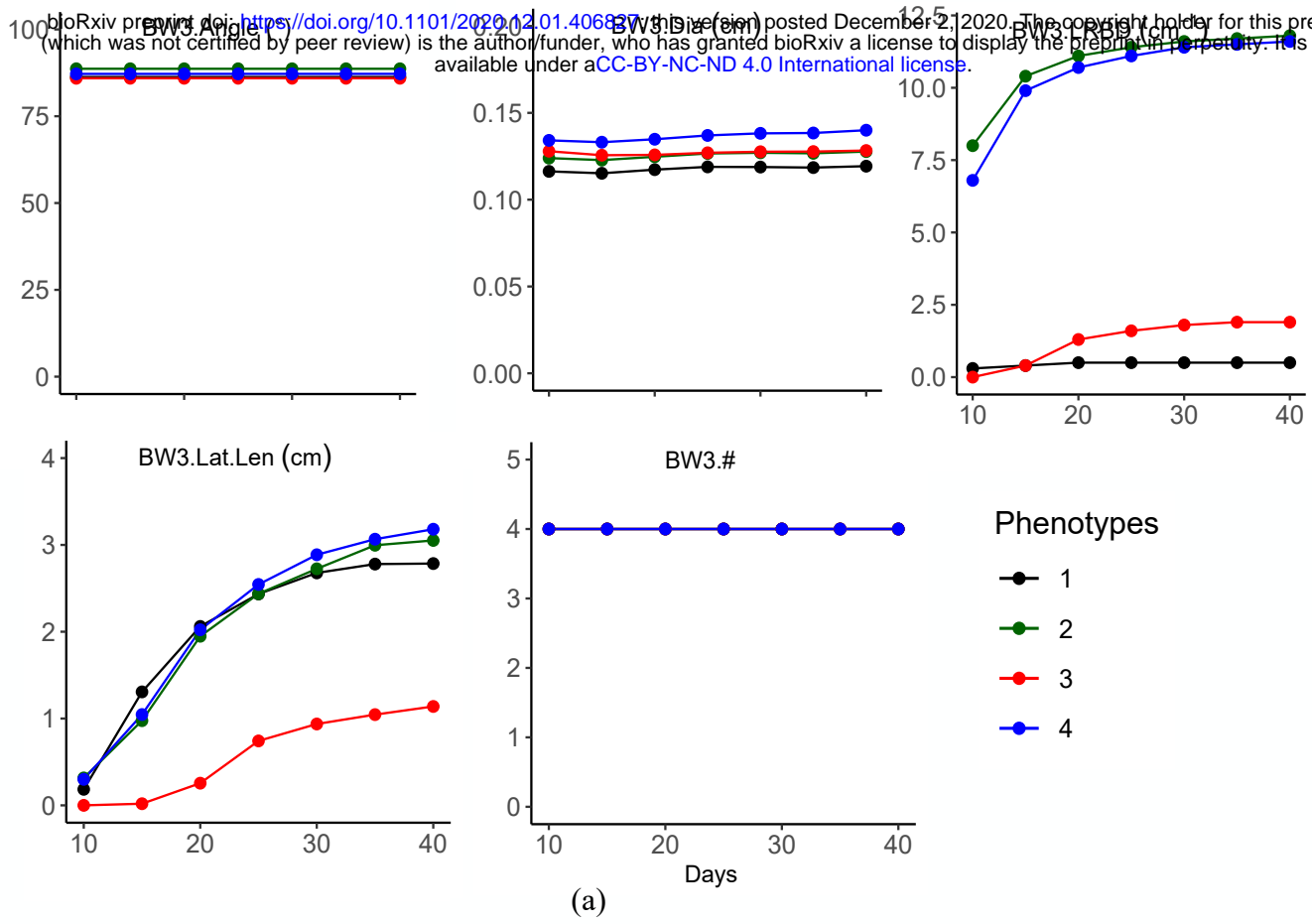


Figure 7: Variation in phene and phene aggregate metrics estimated from rotational series of 2D projected images of 3D root systems of bean (a) and maize (b). BW- Basal root; HBR -hypocotyl-borne root; PR - Primary root; SR- Seminal root; NR Nodal root; # - number of axial roots; Axial.Diam - axial root diameter; Axial.Length - axial root diameter; LRBD - lateral root branching density; Lat.Length - lateral root length; FD - Fractal Dimension; FA Fractal Abundance.



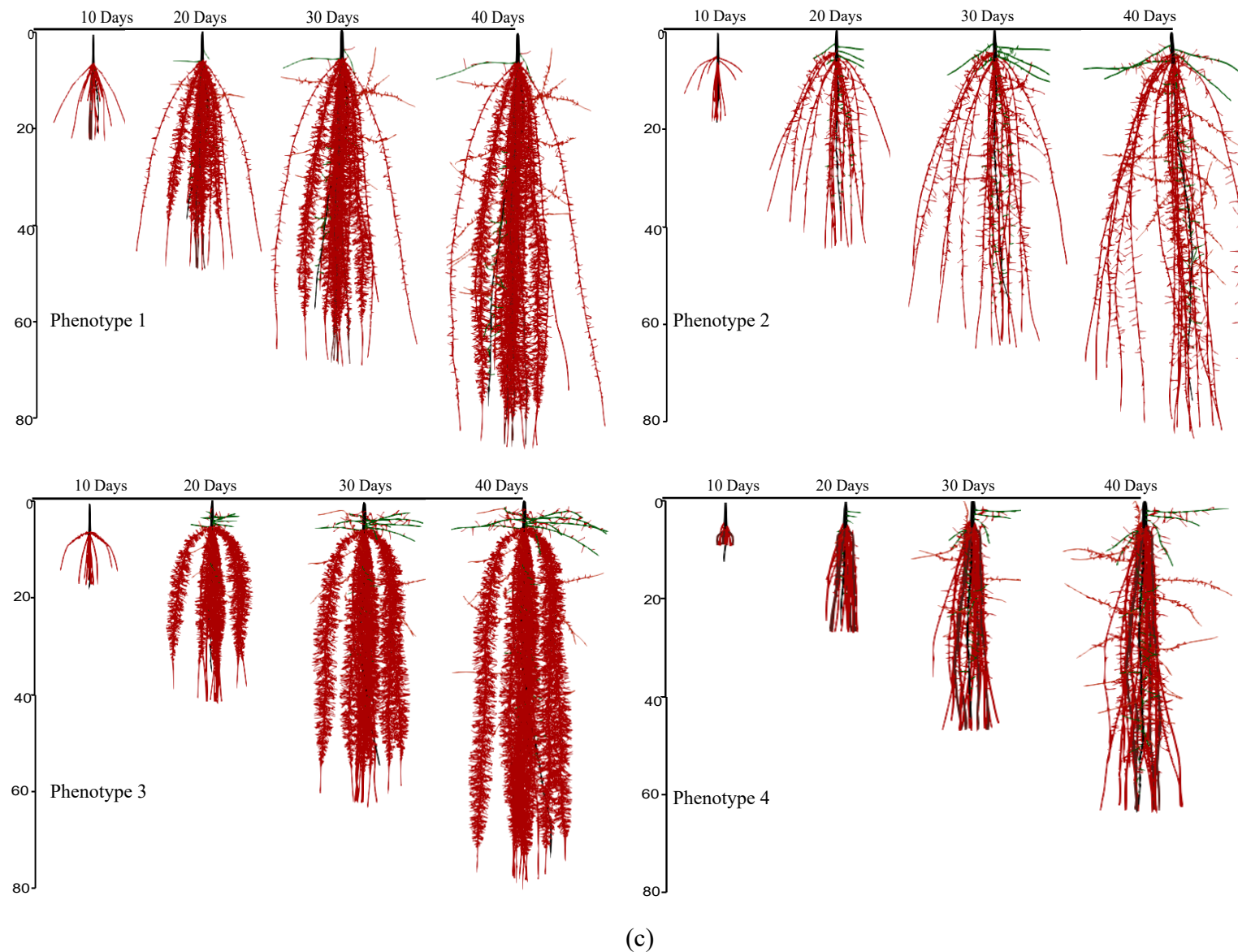
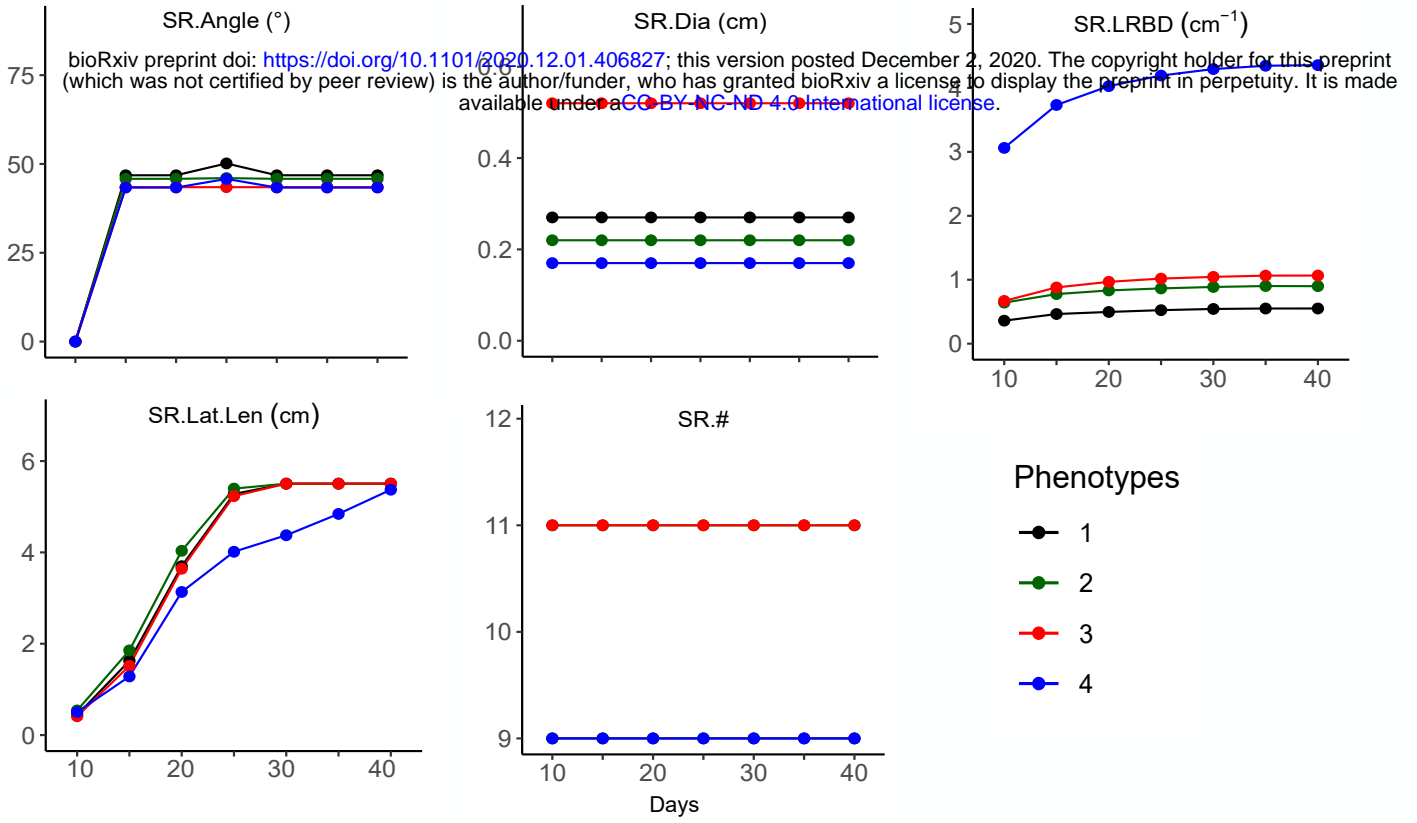
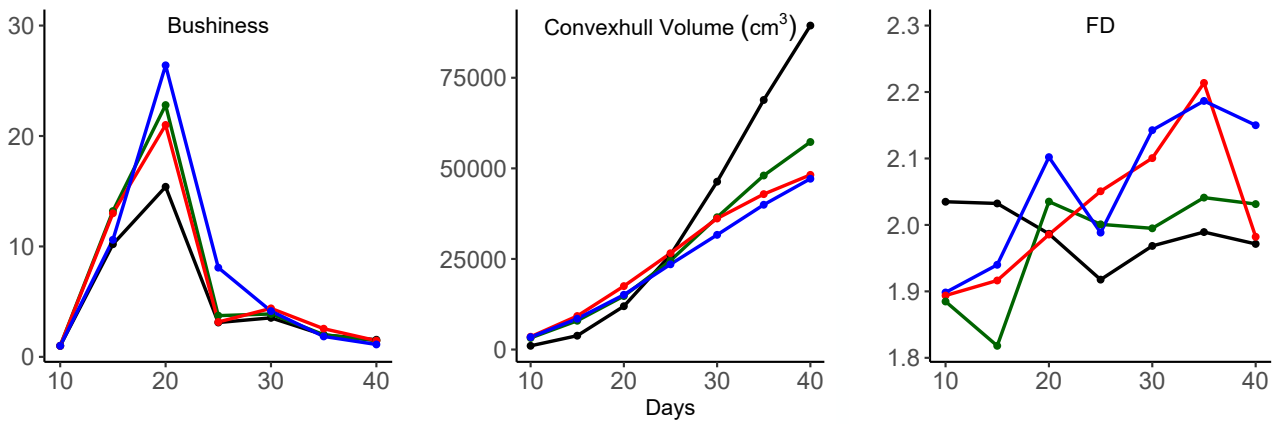


Figure 8: Trait dynamics of bean root phenotypes over 30 days of growth from day 10 to day 40. Change in estimates of phenes associated with basal whorl 3 (BW3) are shown in Figure 8(a). Similar trends were seen in other root classes (Supplementary Figure 4(a)). Change in estimates of the phenes aggregates bushiness index, convexhull volume and fractal dimension (FD) are shown in Figure 8(b). Trends in the estimates of other phenes aggregates included in this study are shown in Supplementary Figure 4(b). The phenotypes for which the metrics are presented in Figure 8(a) and Figure 8(b) are visualized in Figure 8(c). Primary roots are in black; basal roots in red; hypocotyl-borne roots in green. BW3 - basal roots at whorl 3; Dia - axial root diameter; LRBD - lateral root branching density; Lat.Len - lateral root length; # - number of axial roots.



(a)



(b)

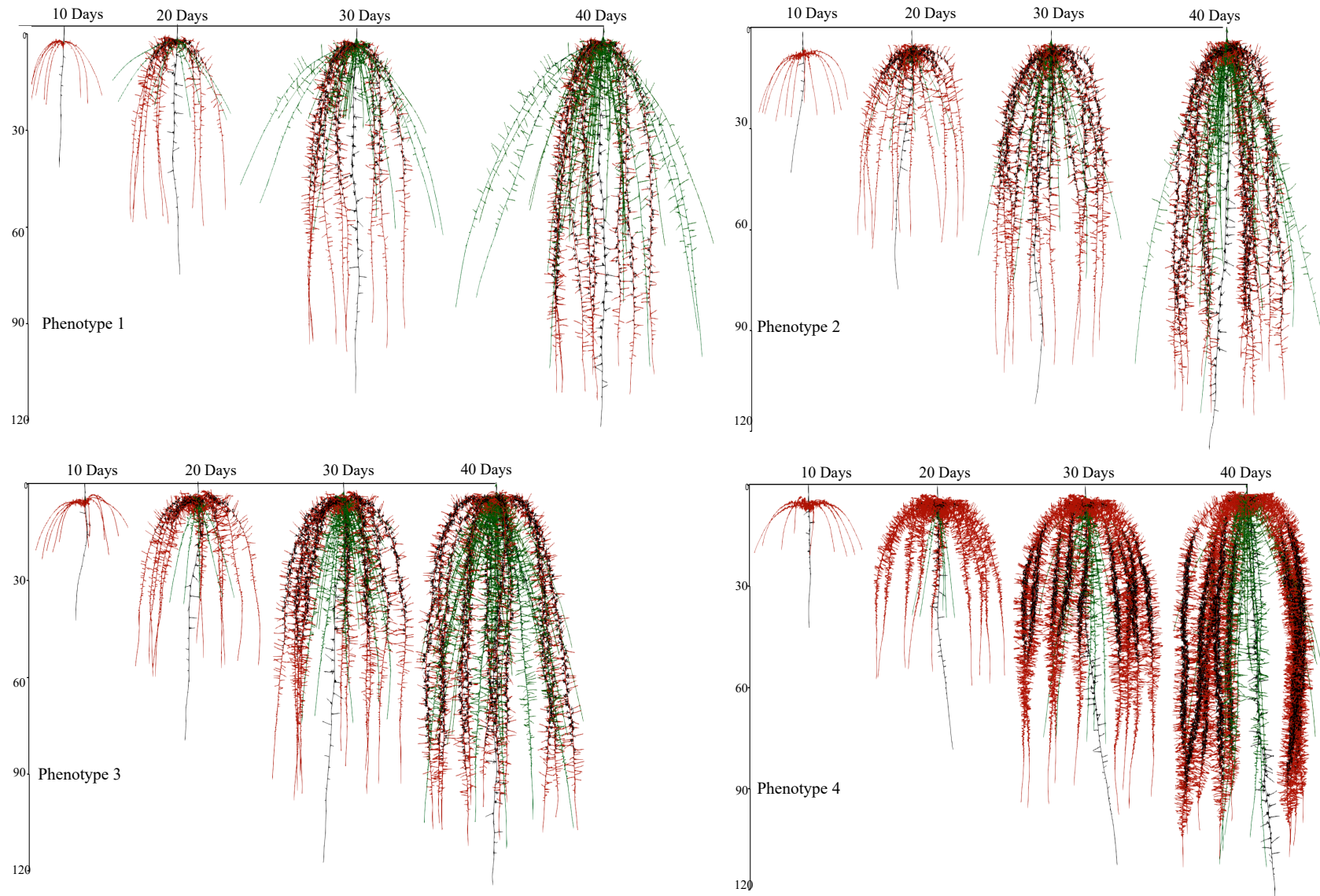
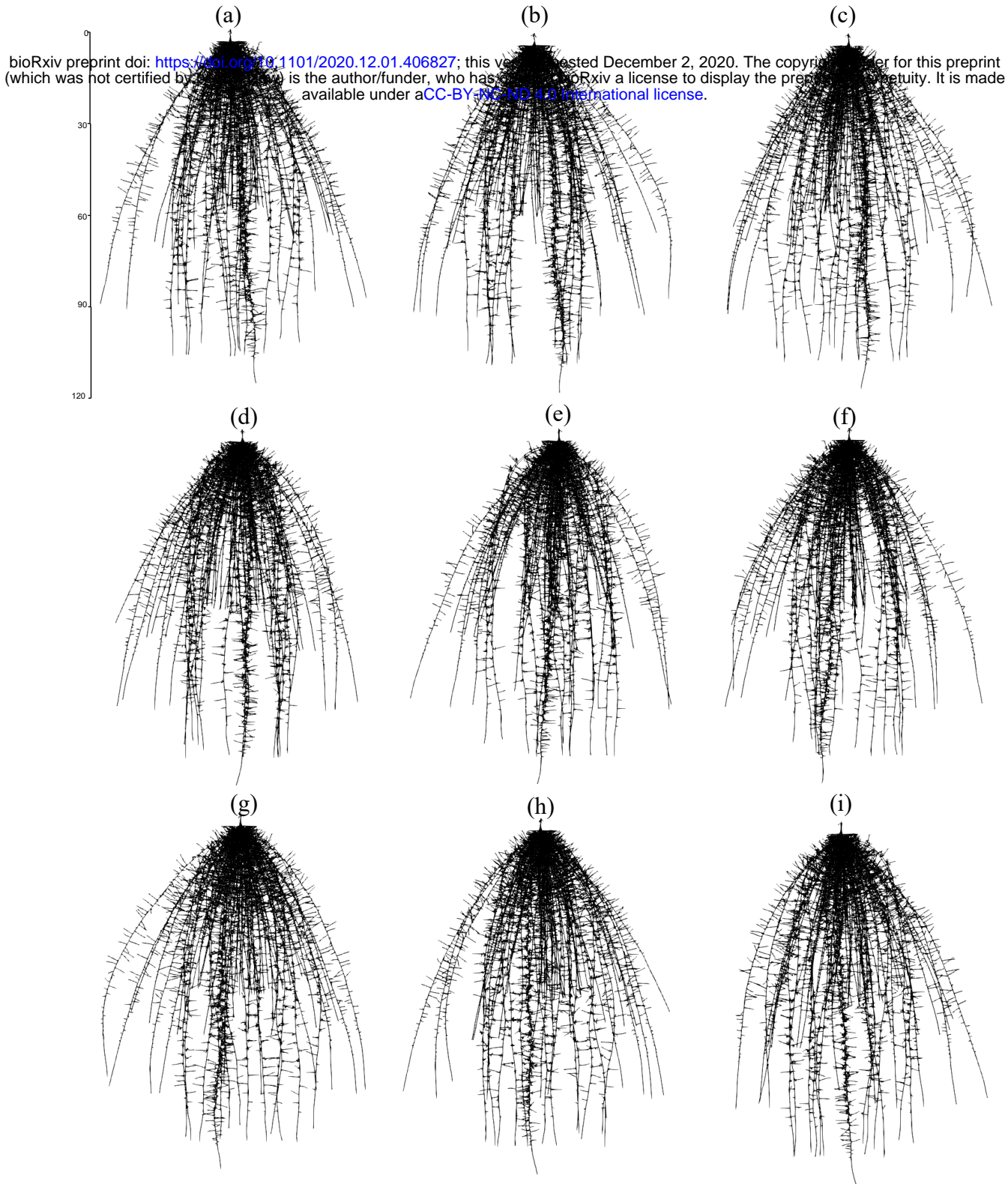


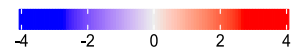
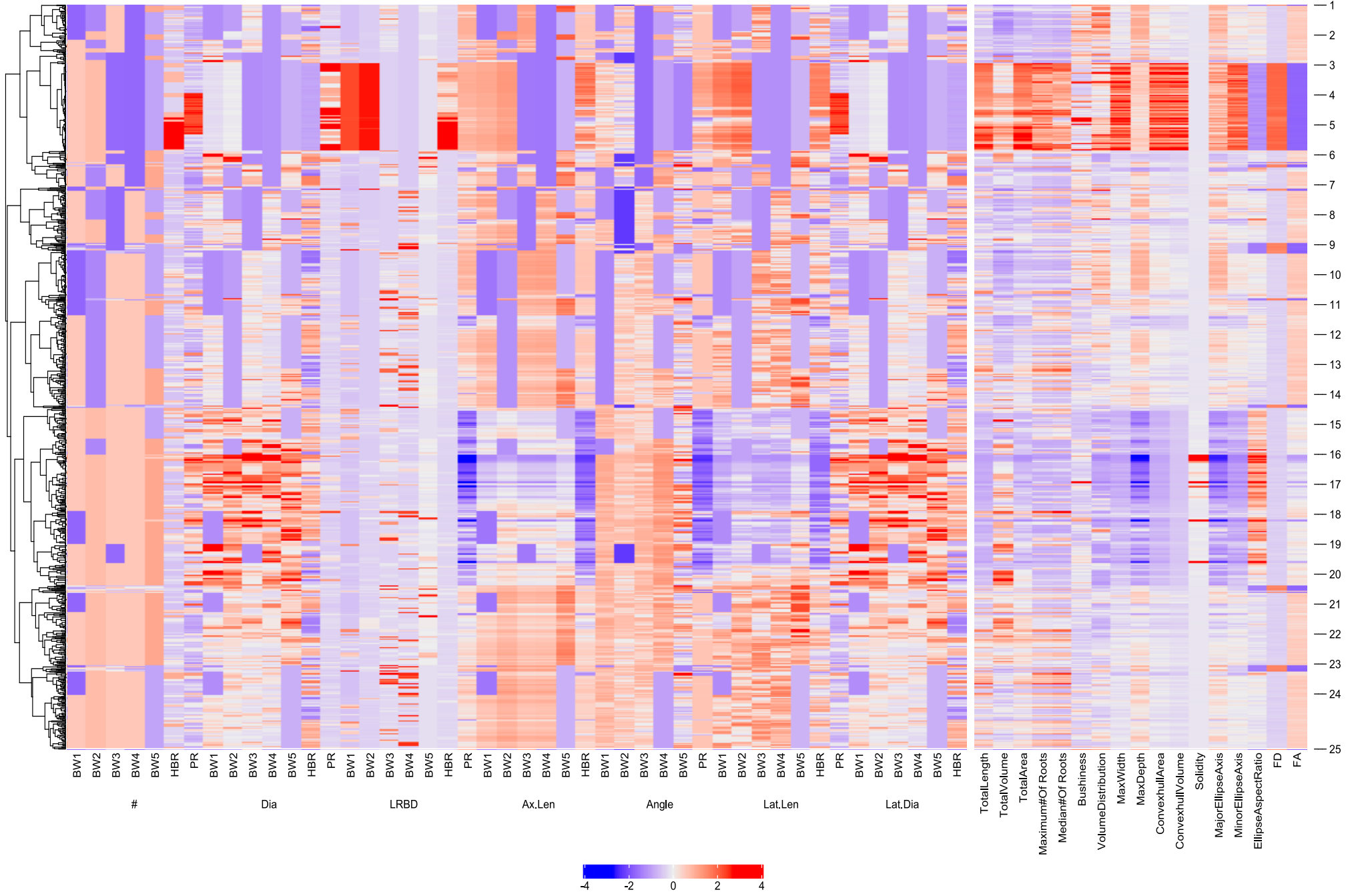
Figure 9: Trait dynamics of maize root phenotypes over 30 days of growth from day 10 to day 40. Change in estimates of phenes associated with seminal roots (SR) are shown in Figure 9(a). Similar trends were seen in other root classes (Supplementary Figure 5(a)). Change in estimates of the phenes aggregates bushiness index, convexhull volume and fractal dimension (FD) are shown in Figure 9(b). Trends in the estimates of other phenes aggregates included in this study are shown in Supplementary Figure 5(b). The phenotypes for which the metrics are presented in Figure 9(a) and (b) are visualized in Figure 9(c). Primary roots are in black; seminal roots in red; nodal roots in green. SR - seminal roots; Dia - axial root diameter; LRBD - lateral root branching density; Lat.Len - lateral root length; # - number of axial roots.



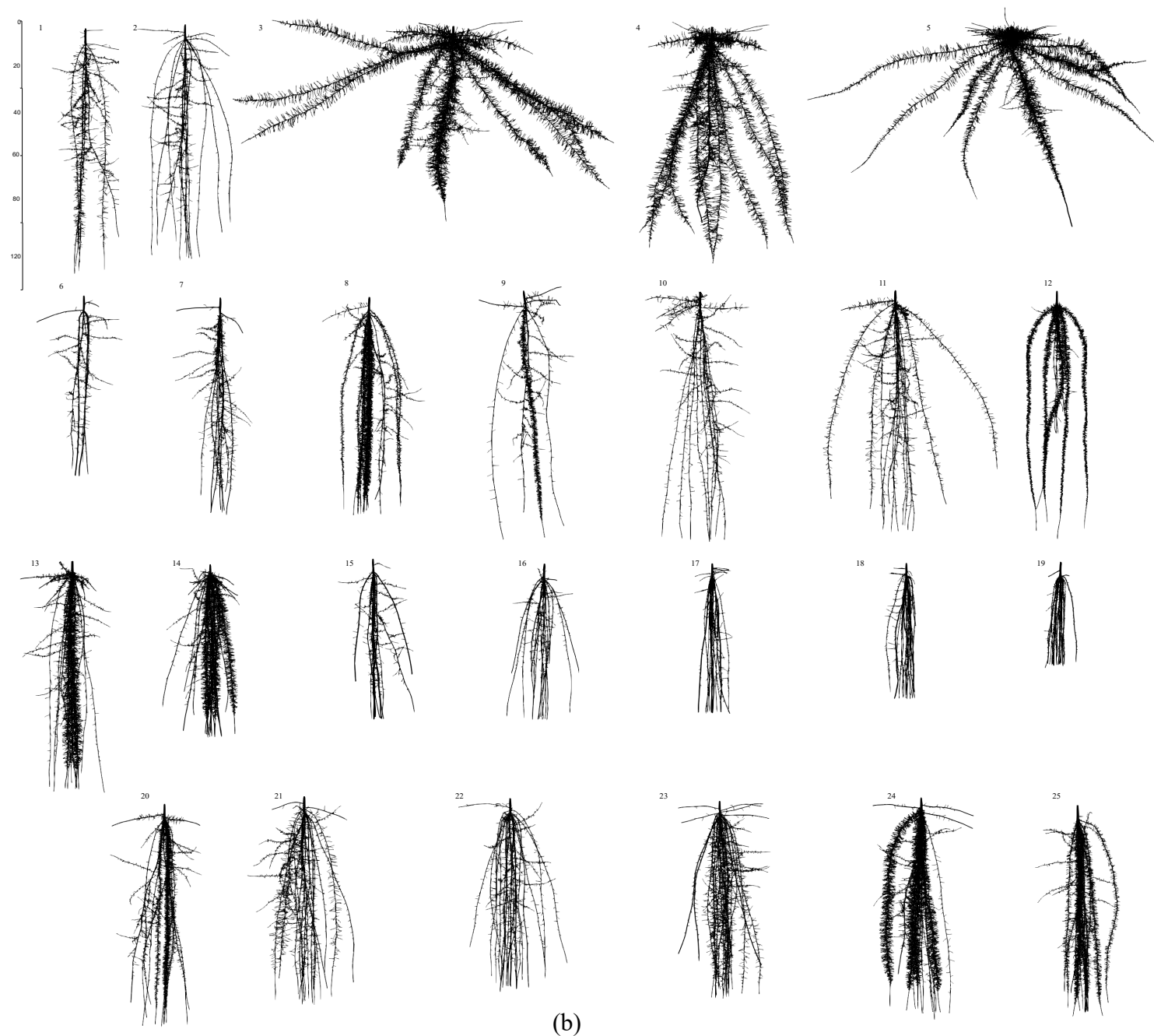
Supplementary Figure 1(a)-1(i): Representative images of 2D projections of a maize root system rotated by 20°, 60°, 100°, 140°, 180°, 220°, 260°, 300°, 340°.

Phenes

Phene Aggregates



(a)



(b)

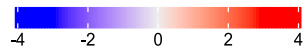
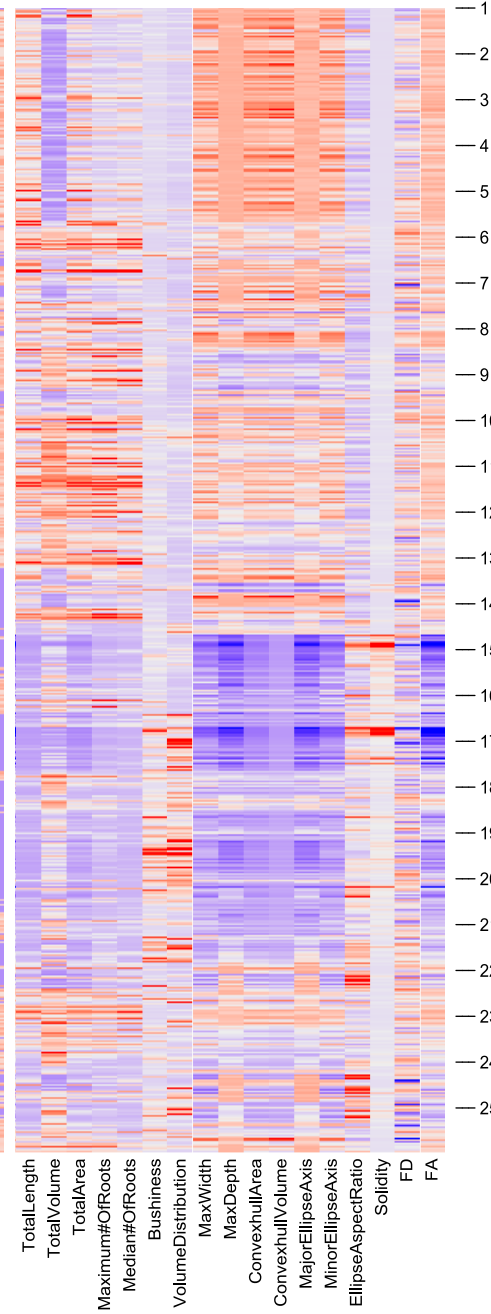
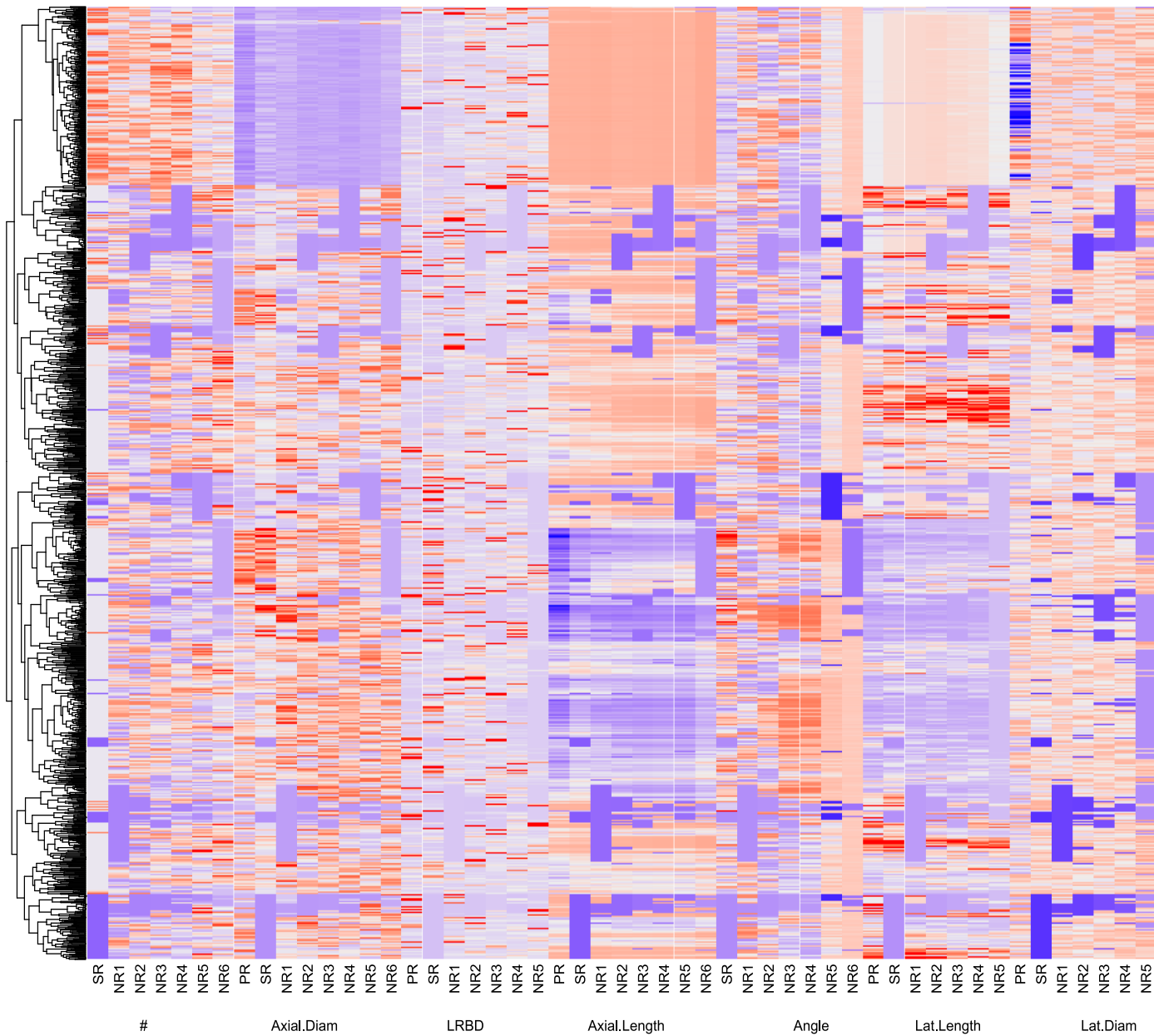
Supplementary Figure 2: Cluster heatmap of phenotypic traits. Hierarchical clustering of all bean phenotypes was generated using Spearman correlation coefficient of max-min scaled phen values at 40 days (a). The color scale indicates the magnitude of the trait values (blue, low value; red, high value).

The numbers indicated on the heatmap refer to a representative phenotype in the specific region of the heatmap. The corresponding phenotypes are visualized in (b).

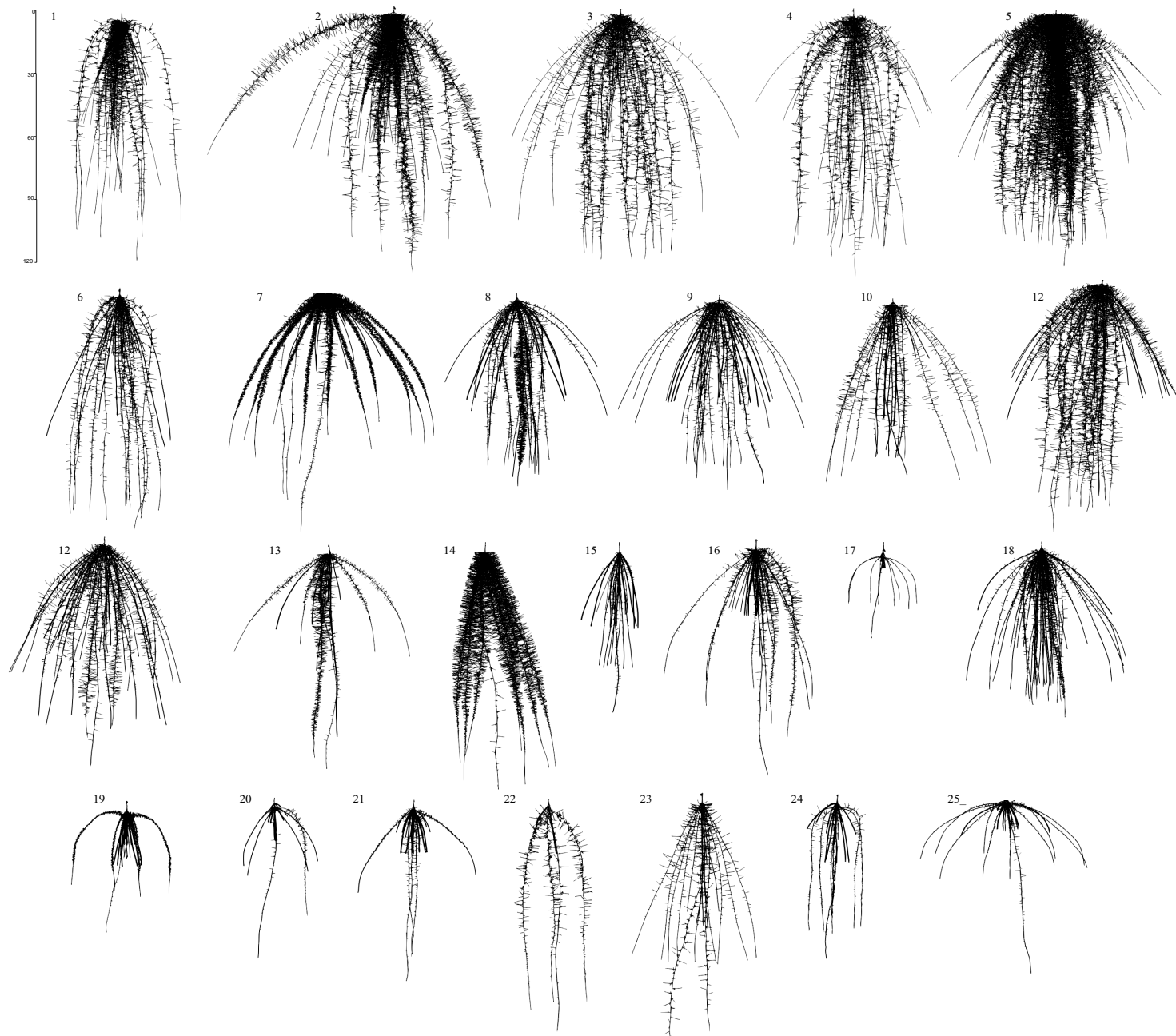
- Number of roots; Axial.Diam - axial root diameter; LRBD - lateral root branching density; Axial.Length - axial root length; Lat.Length- lateral root length; Lat.Diam - lateral root diameter; BW1 - basal roots at whorl 1; BW2 - basal roots at whorl 2; BW3 - basal roots at whorl 3; BW4 - basal roots at whorl 4; BW5 - basal roots at whorl 5; HBR - hypocotyl-borne roots; PR - primary root.

Phenes

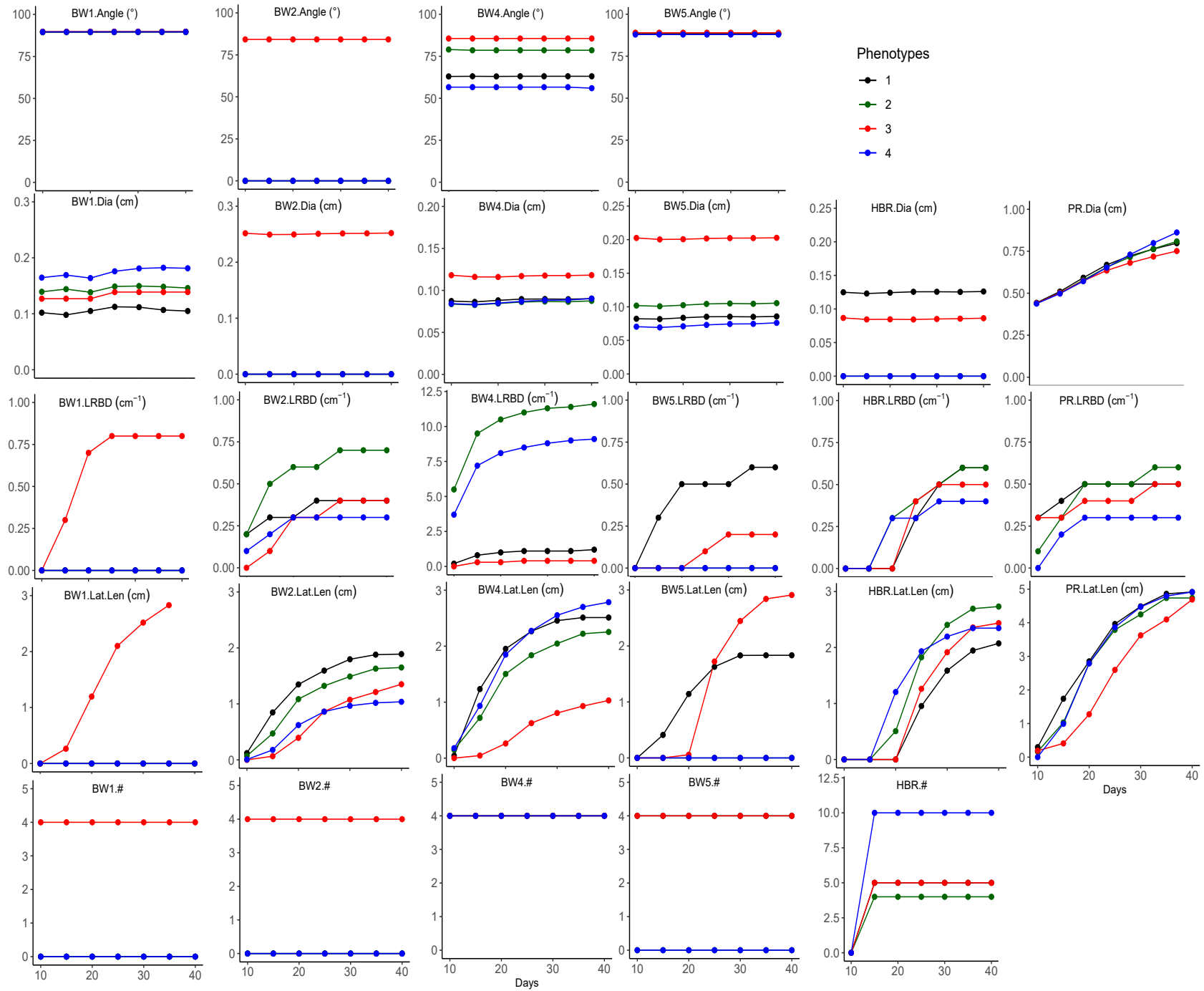
Phene Aggregates



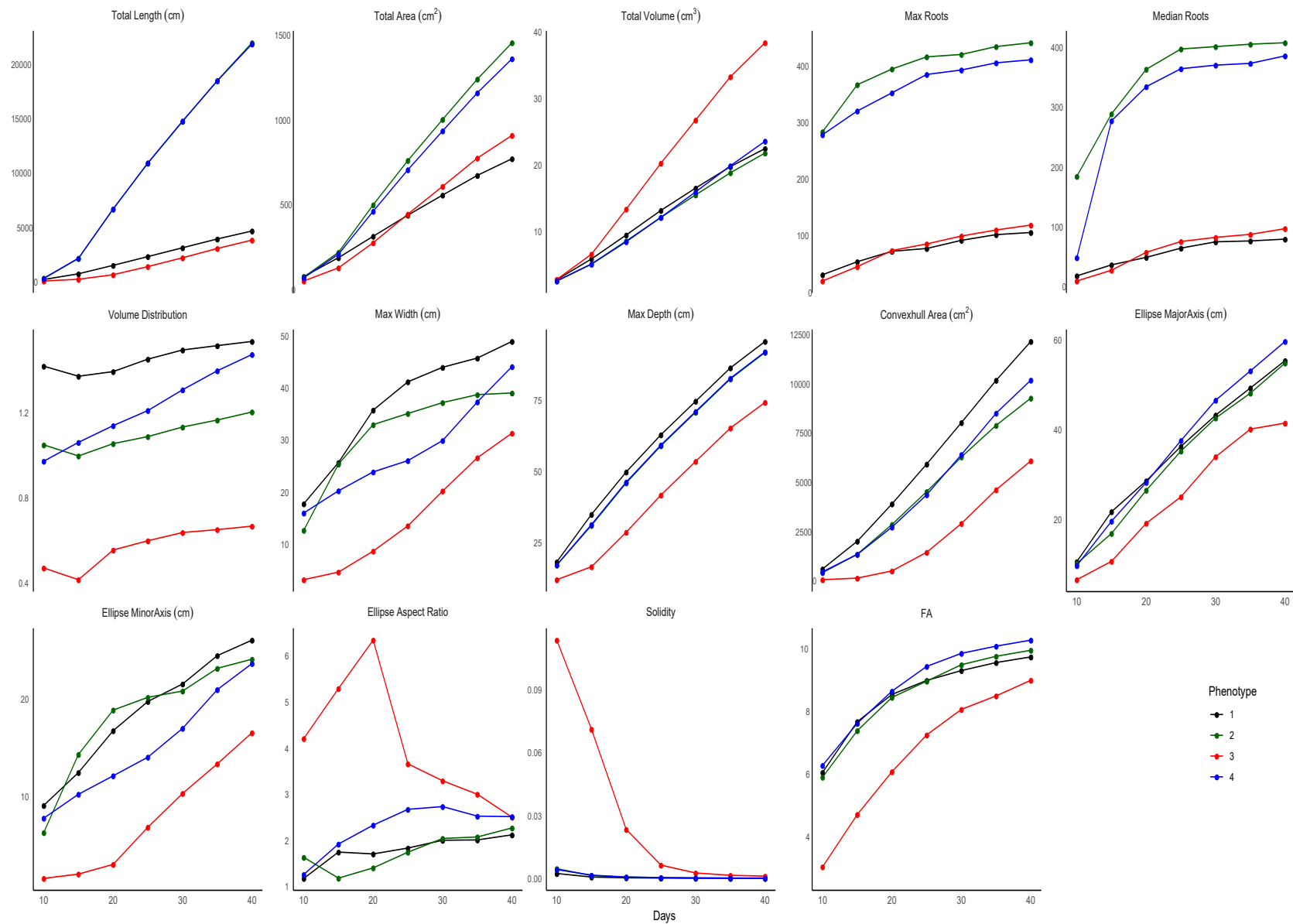
(a)



Supplementary Figure 3: Cluster heatmap of phenotypic traits. Hierarchical clustering of all maize phenotypes was generated using Spearman correlation coefficient of max-min scaled phen values at 40 days (a). The color scale indicates the magnitude of the trait values (blue, low value; red, high value). The numbers indicated on the heatmap refer to a representative phenotype in the specific region of the heatmap. The corresponding phenotypes are visualized in (b). # - Number of roots; Axial.Diam - axial root diameter; LRBD - lateral root branching density; Axial.Length - axial root length; Lat.Length- lateral root length; Lat.Diam - lateral root diameter; NR1 - nodal roots at position 1; NR2 - nodal roots at position 2; NR3 - nodal roots at position 3; NR4 - nodal roots at position 4; SR - seminal roots; PR - primary root.

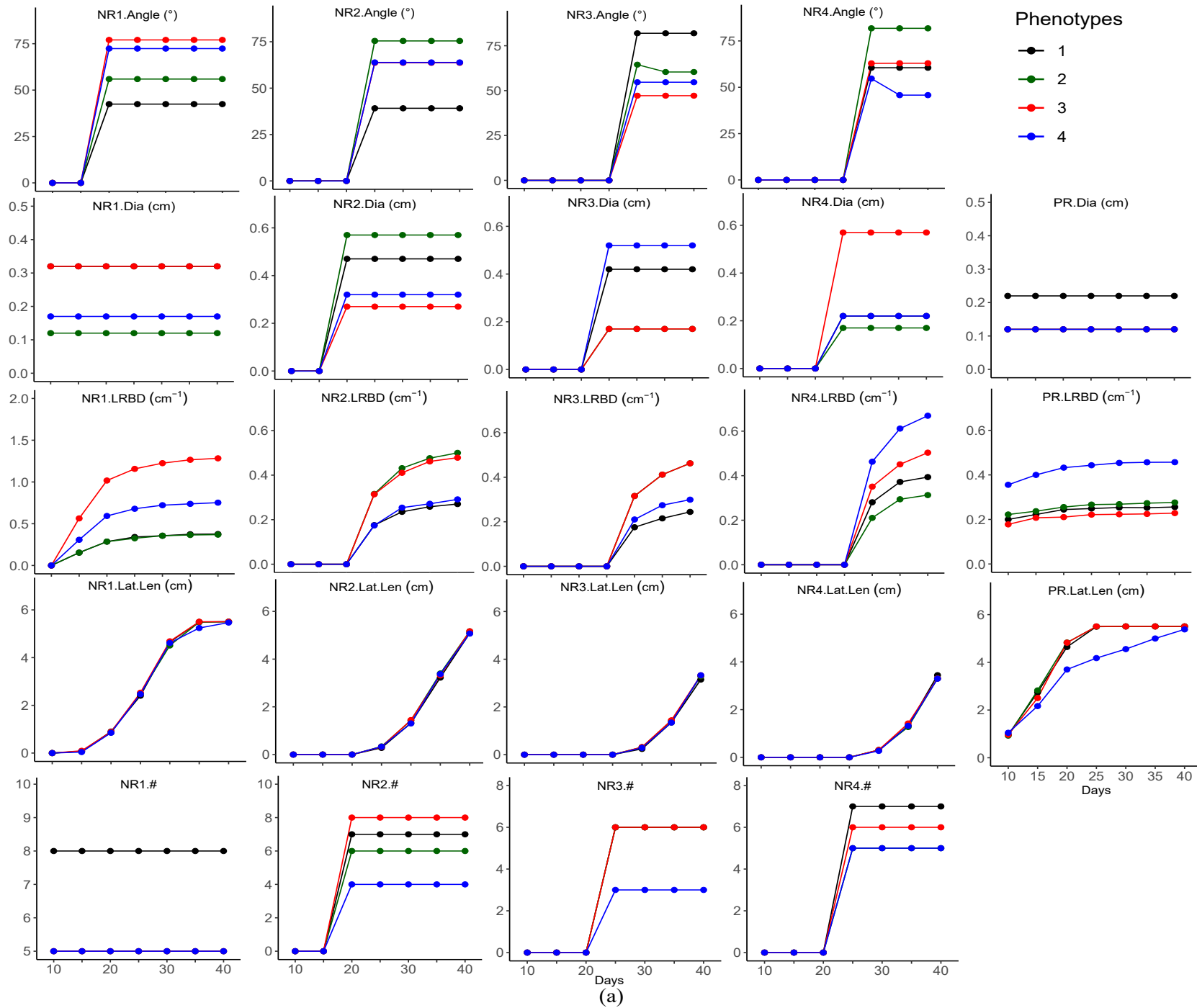


(a)

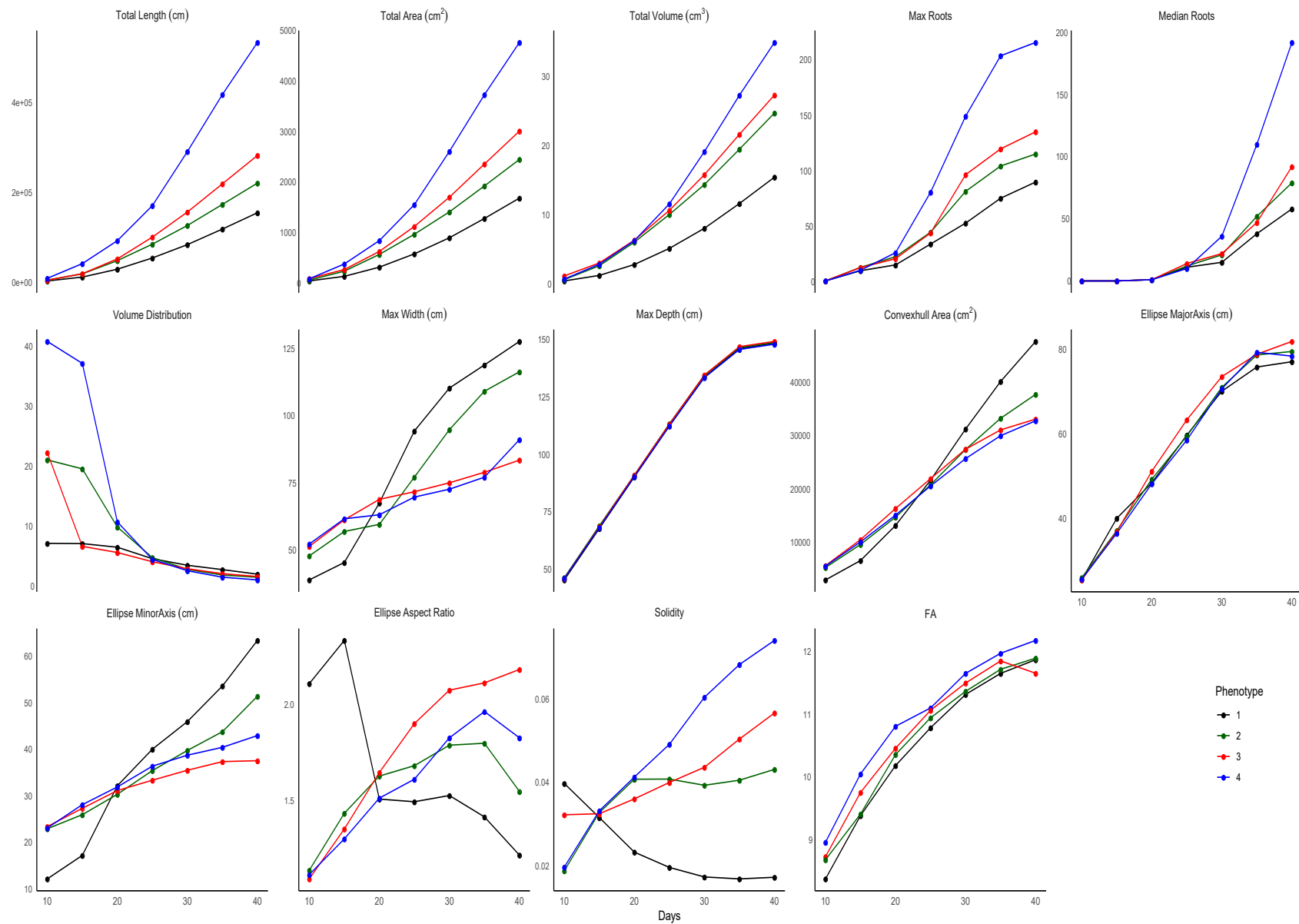


(b)

Supplementary Figure 4: Trait dynamics of bean root phenotypes over 30 days of growth from day 10 to day 40. Change in estimates of phenes (a). Change in estimates of the phene aggregates (b). BW1 - basal roots at whorl 1; BW2 - basal roots at whorl 2; BW4 - basal roots at whorl 4; BW5 - basal roots at whorl 5; HBR - hypocotyl-borne roots; PR - primary root; Dia - axial root diameter; LRBD - lateral root branching density; Lat.Len - lateral root length; # - number of axial roots; FA - fractal abundance.



(a)



Supplementary Figure 5: Trait dynamics of maize root phenotypes over 30 days of growth from day 10 to day 40. Change in estimates of phenes (a). Change in estimates of the phene aggregates (b). NR1 - nodal roots at position 1; NR2 - nodal roots at position 2; NR3 - nodal roots at position 3; NR4 - nodal roots at position 4; PR - primary root; Dia - axial root diameter; LRBD - lateral root branching density; Lat.Len - lateral root length; # - number of axial roots; FA - fractal abundance.