

1 **Title:** Quantitative dissection of color patterning in the foliar ornamental *Coleus* reveals
2 underlying features driving aesthetic value

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4 **Running Title:** Quantitative dissection of color patterning

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43 Summary

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- Coleus is a popular ornamental plant that exhibits a diverse array of foliar color patterns. New cultivars are currently hand selected by both amateur and experienced plant breeders. In this study, we reimagine coleus breeding using a quantitative color analysis framework.
- Despite impressive advances in high-throughput data collection and processing, complex color patterns remain challenging to extract from image datasets. Using a new phenotyping approach called “ColourQuant,” we extract and analyze pigmentation patterns from one of the largest coleus breeding populations in the world.
- Working with this massive dataset, we are able to analyze quantitative relationships between maternal plants and their progeny, identify features that underlie breeder-selections, and collect and compare consumer input on trait preferences.
- This study is one of the most comprehensive explorations into complex color patterning in plant biology and provides new insights and tools for exploring the color pallet of the plant kingdom.

Key words: High-throughput phenotyping, ornamental plant breeding, color patterning, foliar phenotypes, Coleus, color analysis.

89 Introduction

90

91 *Coleus* (*Coleus scutellarioides*) is a common ornamental bedding plant that is bred for
92 its brilliant and diverse foliar color patterning (Bailey, 1924; Pedley & Pedley, 1974;
93 Paton *et al.*, 2018, 2019). Wild relatives in the *Coleus* genus harbor a small degree of
94 variegated pigmentation that has been expanded into distinctive new cultivars that
95 harbor complex variegation patterns through successive rounds of hybridization and
96 selection (Suddee *et al.*, 2004). The prevalence of *Coleus* in gardens and urban
97 landscapes around the world is a testament to the unique aesthetic capacity of this
98 species (Rogers, 2008). With over 500 cultivars on the market, and new ones added
99 each year, *coleus* represents one of the largest and most diverse examples of
100 pigmentation patterning within a single species.

101

102 Advances in plant phenotyping have revolutionized how humans interact with botanical
103 traits (Fahlgren *et al.*, 2015; Gehan & Kellogg, 2017; Gehan *et al.*, 2017; Li *et al.*,
104 2018b; Prunet & Duncan, 2020; Amézquita *et al.*, 2020). High throughput data collection
105 has enabled rapid agricultural trait selection (Singh *et al.*, 2019; Shakoor *et al.*, 2019;
106 Ibba *et al.*, 2020), early detection and management of disease (Mutka & Bart, 2014;
107 Shakoor *et al.*, 2017), and large-scale 2-dimensional morphological analyses (Li *et al.*,
108 2018a). Penetrating high-resolution imaging technologies, such as X-ray CT and laser
109 ablation tomography have also made complex, three-dimensional topologies accessible
110 (Chitwood *et al.*, 2019; Li *et al.*, 2019b, 2020a; Prunet & Duncan, 2020; Amézquita *et*
111 *al.*, 2020; Vanhees *et al.*, 2020). Despite these enormous advances, rapid phenotyping
112 for complex color patterning remains a major hurdle in High Throughput (HTP) analysis.
113 Indeed, the majority of color phenotypes expressed in plants are typically uniformly
114 expressed (for example, monochromatic leaves (Gehan *et al.*, 2017) and berries
115 (Underhill *et al.*, 2020)), un-patterned in their expression (for example, lesions (Arnal
116 Barbedo, 2013; Gobalakrishnan *et al.*, 2020; Xie *et al.*, 2020)), or have highly
117 predictable patterns (for example, nectar guides). These color phenotypes are readily
118 extractable using existing image processing approaches that are not suited for the
119 complex suite of color patterns represented in our *coleus* population (Arnal Barbedo,
120 2013; Gobalakrishnan *et al.*, 2020; Xie *et al.*, 2020)). Here, we address the need for

121 enhanced tools to extract and analyze complex patterns. In this study, we map out
122 pigmentation values as three-dimensional point clouds in Lab color space, extract the
123 continuous distribution of color using Gaussian density estimation (Li *et al.*, 2019a),
124 dissect color patterns based on pigmentation position on two dimensional leaves,
125 quantify bilateral symmetry for shape and color, and separate shape from color using
126 thin plate spline deformation.

127
128 Given the prominence of Coleus in the gardening marketplace, and the vast diversity of
129 pigmentation patterns that are exhibited within Coleus breeding populations, Coleus as
130 a breeding system serves as an ideal platform for testing this new, quantitative
131 approach for HTP color phenotyping. In this study, we develop a pipeline to extract
132 quantitative descriptors for foliar pigmentation patterns from one of the largest Coleus
133 breeding populations in the world ($n > 32,800$ plants). We are able to extract the
134 distribution of all existing pigmentation patterns presented within this massive breeding
135 population, quantify maternal plant-progeny pigmentation relationships, and identify
136 aesthetic features that are associated with increased value from the perspective of the
137 breeder as well as the general public. This work is built on a powerful study system, and
138 provides a new framework for approaching complex color phenotyping. This work has
139 direct implications for investigating color features in both ornamental plant breeding and
140 ecological systems, where pigmentation patterns play an important role in influencing
141 how plants interact with humans, pollinators, and herbivores.

142

143 **Methods**

144

145 **Coleus population, sampling, and image processing**

146

147 We collected and sowed 50,000 Coleus seeds from 133 open-pollinated mother plants
148 in early January, 2015 in Gainesville, FL. We organized the seedlings into families
149 based on their maternal parents, grew the plants for five weeks and then selected
150 ~2,000 individuals as potential new cultivars based on their foliar color patterning and
151 branching architecture in mid-February. Next, we harvested the youngest fully

152 expanded leaf from each plant between 5-6 weeks of age, and imaged the leaves on
153 Epson Perfection V550 Scanners with Kodak KOCSGS color separation guides
154 included for color calibration (Supplemental Fig 1; data available here: Zenodo.org
155 10.5281/zenodo.4421754). We performed color analysis using our open-access
156 software program called ColourQuant (Li *et al.*, 2019a); software available on github:
157 github.com/maoli0923/ColourQuant). Briefly, we adjusted the RGB color balance on
158 each scan by a white balance method so that the white swatch in the Kodak KOCSGS
159 color separation guide is pure white, to ensure that scanners were not biasing the color
160 data. Next, we segmented the leaves from the background by converting the RGB
161 matrix into hue-saturation-value (HSV) format. Since most background pixels are grey in
162 HSV, this was used to set a threshold (e.g. $S > 0.15$) that separates grey values from true
163 leaf values. We then used the binary leaf silhouettes to extract the leaf color data by
164 setting the background to pure white. We manually adjusted the thresholding for leaves
165 that could not be automatically extracted due to shadows in the scan, and removed
166 outliers from the sample set, including leaves that were overlapping on the scanner,
167 very small, or broken.

168

169 **Color pattern analysis**

170

171 To extract quantitative color distribution information, we converted the leaf color
172 matrices from RGB to CIELAB ($L^*a^*b^*$) color, which is a continuous color space that
173 consists of three descriptors: L^* = “lightness,” a^* = “green to magenta,” and b^* = “blue to
174 yellow.” We studied the distribution of mean and variance for L^* , a^* , b^* color values
175 across the leaves by first calculating the average value and variance of L^* , a^* , and b^* for
176 each leaf (i.e. “mean L^* ,” “mean a^* ,” “mean b^* ,” “variance of L^* ,” “variance of a^* ,” and
177 “variance of b^* ”), and then plotting histograms and boxplots to show the overall mean
178 and variance distributions for all leaves in the breeding population. Next, we treated the
179 3D Lab color matrices as 3D point clouds, which enabled us to extract color distribution
180 and frequency information for each leaf.

181

182 The mean and variance of Lab values roughly describes the color for each leaf.
183 However, in order to compare the distribution and frequency of Lab values across the
184 leaves, we applied a Gaussian density estimator (GDE) to the Lab point cloud. GDE is
185 a function defined on 3D space, providing a robust and direct density estimate from the
186 point cloud data. To reduce computational complexity, we restricted the domain of the
187 GDE function to a fixed bounded cuboid. The GDE descriptor alone captures statistical
188 color frequency, not spatial patterning. To capture spatial color information, we
189 segmented the leaves into distinct zones based on normalized pixel distances: “border”
190 – defined as the outer 15% of pixels from the leaf boundary to the centroid, “center” –
191 defined as the inner 75% of pixels from the centroid to the boundary, and “full” – defined
192 as the entire color matrix. The distance between any two leaflets is calculated with the
193 following equation:

194

$$195 \quad D = \sqrt{d_{full}^2 + d_{border}^2 + d_{center}^2}$$

196

197 where d represents the L_2 distance between GDE functions for each corresponding
198 zone. With this calculation, the pattern difference between two leaves is determined by
199 their degree of similarity across all three zones. For pairwise distances, we used
200 multidimensional scaling (MDS, similar to a PCA) to project the data in a lower
201 dimensional space, which allows us to capture the major features that contribute to
202 pattern variation. These methods and the supporting software for this approach can also
203 be found in the publication by (Li *et al.*, 2019a)
204 (<https://github.com/maoli0923/ColourQuant>).

205

206 To quantify the degree of mirror symmetry for each leaf, we first marked a bilaterally
207 symmetric line by placing two landmarks, one at the proximal point (petiole) and another
208 at the distal point (leaf tip). These landmarks were then used to partition the leaf into
209 longitudinal halves that could be directly compared to one another. We used two
210 methods for quantifying mirror symmetry. First, we performed a general measure by
211 comparing the differences in left and right color distributions (using GDE functions), and

212 second, we measured the degree of bilateral shape symmetry by overlaying the left and
213 right halves of the leaf and computing the percentage of pixels that fail to overlap.
214 Notably, smaller values reflect a lower degree of asymmetry.

215

216 **Quantitative analysis of maternal-offspring pigmentation relationships**

217

218 To calculate the phenotypic distance between maternal plants and their progeny, we
219 divided the distance between each maternal leaf and the leaves of its progeny by the
220 distance between the maternal leaf and all of the leaves in the breeding population. To
221 investigate how maternal color and color complexity influence these color traits in the
222 progeny population, we calculated the mean and variance of L^* , a^* , and b^* for the
223 maternal leaves and their offspring and then computed the variance of those traits
224 across the offspring within each family (e.g. named as “variance of family mean L ”, and
225 “variance of family L variance”).

226

227 **Quantifying aesthetic features of selected plants**

228

229 We calculated the influence of breeder selection on color and shape symmetry, as well
230 as pigmentation L^* , a^* , and b^* values, by comparing the probability distribution for each
231 value in the entire breeding population with the probability distribution in the selected
232 population. Two sample T-tests accounting for uneven sample sizes were used to
233 calculate the significance of selection on each color parameter.

234

235 **Public preferences for coleus colors independent of shape**

236

237 To investigate color preferences amongst the general public, we created a survey
238 based on the major sources of variation for leaf color patterning. First, we separated
239 shape from color patterning by deforming the leaves into uniform circles using thin-
240 plate-spline (TPS) interpolation, followed by centering and normalizing the circles into
241 the same position and size. Next, we rotated each circularized leaf so that the first
242 landmark (near the base) is on the negative half of the y axis ($x=0$) and the tip is on the

243 positive half . We resized each circular leaf image to be 70x70 dimension and reshaped
244 the pixel L*a*b* colors into a long (12150 dimension) vector. To calculate the main
245 sources of variance, we performed a principal component analysis on the long vectors
246 of the circularized leaves and created a survey using google forms where public
247 volunteers were asked to select their preference of eigencolors for the top 8 principal
248 components (PCs). For kth PC, the eigencolors are represented by $\pm x$ standard
249 deviation along PC axis, where $x=3+(k-1)*0.5$, this produced more distinct color variants
250 for the survey participants . We distributed the survey using a dedicated Twitter account
251 (@ColeusColours), and then plotted the responses from all of the survey participants
252 (N=172) and reconstructed the composite preferred leaf based on the responses.

253

254

255 **Results**

256

257 **New coleus breeding population**

258

259 Coleus is one of the most diverse species with regards to leaf pigmentation patterning in
260 the world. Brilliant new coleus cultivars harboring novel leaf color and shape
261 phenotypes can be generated using a recurrent mass selection approach. In this study,
262 we took advantage of a very large coleus breeding population in order to explore the full
263 spectrum of possible pigmentation patterns and their influence on breeding processes.
264 We used 133 open-pollinated elite coleus lines that exhibit a wide range of existing color
265 and shape phenotypes (Fig 1A-B) to generate a large population that harbors novel
266 pigmentation combinations. To capture these new combinations, we planted over
267 32,000 F1 progeny, and imaged their leaves on high-resolution color scanners
268 (supplemental Fig S1). Color data are typically recorded as a composite of discrete
269 Red, Green, and Blue (RGB) values that range from 0-255. We transformed our RGB
270 data into the continuous Lab color space, which we then treated as a three-dimensional
271 point cloud and extracted quantitative pigmentation data using a Gaussian density
272 estimator (GDE) function (Fig 1C). A GDE function is a smoothed version of a
273 histogram; it estimates data density by summing all of the normal distributions, which

274 are placed on each data point. Higher values are produced from regions with more data
275 points, while lower values are produced from regions with sparse and/or noisy data,
276 thus making the function robust.

277
278 To visualize the CIELAB ($L^*a^*b^*$) color space within our breeding population, we plotted
279 the mean values of L^* (lightness), a^* (green-to-magenta), and b^* (blue-to-yellow) that
280 were extracted from each leaf. The majority of leaves within the population skewed
281 towards darker (lower) mean L values (Fig 2A). Mean values for a^* spanned from
282 magenta-to-green, but were more heavily concentrated towards the magenta/maroon
283 half of the range (Fig 2B), and mean values for b^* were almost exclusively in the
284 positive range, and were strongly concentrated towards yellow rather than blue values
285 (Fig 2C). While this approach provides an estimate of mean color distributions, it fails to
286 capture color patterning within the population (Fig S2). There are three discrete regions
287 that can be used to generally describe that vast majority of variegation patterns in
288 coleus: the area surrounding the veins, the leaf border, and the leaf center. We applied
289 a Gaussian density estimator function to 3-dimensional point clouds of the border (15%
290 of pixels from the leaf boundary) and center (75% of the pixels from the centroid)
291 regions of the leaf (Fig 1C). Venation varies considerably from leaf-to-leaf, and thus it is
292 challenging to consistently extract this value from a large population, so we did not
293 consider the contribution of variegated venation for this study. Our isolated border and
294 center regions differed significantly from the full variance of $L^*a^*b^*$ values (P ranged
295 from 7.75×10^{-4} to $< 2.23 \times 10^{-308}$), indicating that these regions exhibit distinct color
296 patterns (Fig 2D). Multidimensional scaling (MDS) can be used to extract the main
297 sources of variance within complex datasets. To investigate the variance in color
298 patterning within our population, we generated MDS plots from the GDE function
299 distance for the full leaf (Supplemental Fig S3A), border (Supplemental Fig S3B), center
300 (Supplemental Fig S3C), and composite full leaf plus border plus center distance (Fig
301 2E-H). We have superimposed example leaves on top of the plot to illustrate the major
302 color differences that are represented within the population (Fig 2F, H, and S3).

303

304 The sub-sample border and center plots provided poor separation of the major pattern
305 classes within the population (Supplemental Fig S3B-C). For example, green bordered
306 leaves with maroon centers are distributed in multiple locations across the border and
307 center MDS plots (Supplemental Fig S3B-C). The full leaf plot performed much better
308 with regard to pattern separation compared to the sub-sample plots; however, it still
309 failed to produce distinct groupings for detailed pattern differences. For instance, pink
310 and maroon center variegation patterns are intermixed with solid maroon leaves in all 4
311 dimensions of the full leaf MDS (Fig S3A). The composite plot, on the other hand,
312 accounts for both global and isolated center and border pigmentation values, and thus
313 was able to resolve distinct pattern groupings (Fig 2E-H). The first dimension clearly
314 separates the population along the green-to-magenta divide (the a^* value of the $L^*a^*b^*$
315 color space), while the second dimension separates the population from darker
316 (towards the bottom) to lighter L^* pixel distributions (Fig 2F). In the third and fourth
317 dimensions, five major patterns are resolved: solid orange in the upper right, solid deep
318 purple in the upper left, solid green in the lower left, solid maroon in the lower right, and
319 several sub-populations of variegated patterns in the lower left and center (Fig 2H). In
320 the lower left corner of MD 3 and MD 4, we were able to resolve most of the variegated
321 patterns into subpopulations based on center and border features, for example wide
322 maroon centers with thin green borders, light pink centers with green, maroon, or
323 orange borders, yellow/white centers with green borders, and even deep purple
324 venation on green leaves. There are, however, two pigmentation patterns that we failed
325 to isolate in our composite plot. First, are leaves that have both relatively small central
326 pigmentation regions and low contrast between the border and center colors, and
327 second, are leaves with random green and purple sectors whose patterns were most
328 likely generated by active transposons (Tilney-Bassett & Others, 1986; Frank &
329 Chitwood, 2016). Overall, this composite MDS approach performed very well with
330 regard to separating the population into major pattern groups.

331

332 **Maternal phenotypes influence the phenotypic distance of their progeny**

333

334 The vast majority of brilliant new coleus color patterns result from the spatially regulated
335 production of anthocyanin (purple and pink pigments) and loss of chlorophyll (white and
336 yellow pigments). Classic genetic analyses indicate that purple pigmentation is
337 controlled by a single dominant allele, while loss of chlorophyll pigmentation resulting in
338 yellow/albino phenotypes results from a recessive allele (Boye & Rife, 1938; Rife,
339 1948). These studies were carried out in simplified phenotypic and genetic
340 backgrounds; however, they provide a basic framework for interpreting the color
341 relationships within our large breeding population. To address patterning relationships
342 within our population of 32,000+ individuals, we quantified the relative distance between
343 maternal plants and their progeny and visualized it in multidimensional scaling (MDS)
344 space (Fig 3). It is important for us to note that our population was generated using an
345 uncontrolled, open-pollination design; honeybee hives were brought into the field to
346 ensure pollination and promote outcrossing amongst the maternal plants. In our field
347 setting, it is impossible to track the male half of the parental equation without the
348 developing genotype-specific molecular markers, so we are only analyzing maternal-to-
349 progeny relationships. Another limitation that we cannot exclude from this experimental
350 design is the potential bias that leaf patterning can have on pollinator behavior, and
351 while we cannot assume true random mating within this context, we have reason to
352 believe that pollination behavior is close to random based on the fact that coleus flowers
353 tend to be highly conserved with respect to their morphology and color. Thus, they are
354 likely equally attractive to our honey bee pollinators.

355
356 We identified a few clear trends from our mother-child analysis. First, brighter maternal
357 plants (high L^*) tend to produce progeny with a greater variance of pixel brightness (Fig.
358 S4A). This is exemplified by the progeny in families 79 and 43. We also observed that
359 green maternal plants (low a^*) tend to produce progeny that exhibit a large variance
360 between green and magenta (Fig. S4B, for example, the progeny in families 43 and 94).
361 This is logical, given that purple and magenta pigments have been linked to dominant
362 alleles, and thus would be expressed in F1 crosses with purple/magenta pollen donors.
363 Along similar lines, yellow maternal plants (high b^*) tend to produce progeny that
364 express a large variance in the yellow-to-blue color range (Fig. S4C, for example the

365 progeny in families 79 and 29). Again, this follows the logic that yellow pigmentation is a
366 recessive trait, and thus color patterning in the F1 generation is more likely to exhibit
367 paternal phenotypes. We found that maternal plants with complex color patterning (high
368 variance of L^* , a^* , or b^*) tend to produce progeny with larger variance in their complexity
369 (Fig. S4D-F, for example the progeny in families 22 and 23), which results in more
370 diverse color patterns. Surprisingly, we only saw a minor trend for green versus purple
371 maternal plants being closer versus farther away (respectively) from their progeny in
372 phenotypic space. The majority of green leafed maternal plants fall on the top half of the
373 phenotypic distance plot (e.g. smaller distance, for example, the progeny in families 63,
374 43, 94, 79, and 15), while purple maternal plants are distributed across the phenotypic
375 spectrum (Fig 3).

376

377

378 **Bilateral symmetry for color and shape are strongly correlated with the selection** 379 **of new cultivars**

380

381 New coleus cultivars are hand selected based on the visual identification of target traits,
382 through a process that is frequently referred to as selection via “the breeder’s eye”
383 (Fasoula *et al.*, 2019). Our experienced coleus breeder identified approximately 2,000
384 selected lines from the population to carry forward for potential cultivar development. A
385 long-standing theory posits that symmetry is positively correlated with aesthetic value
386 (Birkhoff, 1933). To investigate the influence of color and shape symmetry on our
387 breeding process, we tested whether our selected population deviated significantly from
388 the total population with regard to color and shape symmetry, as well as mean Lab
389 distributions (Fig 4).

390

391 To quantify the degree of mirror symmetry within leaves from the selected versus total
392 population we manually partitioned every leaf into left and right halves by drawing a line
393 from the tip to the base of the leaf. We then quantified color asymmetry by comparing
394 the Lab Gaussian distributions between the left and right halves (Fig 4A), and shape
395 symmetry by folding binary leaf silhouettes along the midline and calculating the

396 percentage of non-overlapped pixels (Fig 4B). Our two sample T-tests between the
397 selected and total population showed very strong statistical support for both color and
398 shape symmetry playing a significant role in influencing the selection process (p-value
399 $9.72e-05$ for increased color symmetry, and $p\text{-value}=6.01e-51$ for increased shape
400 symmetry in the selected population; Fig 4C).

401
402 To determine if specific color features correlated with cultivar selection, we tested
403 whether the selected pool differed from the total population with regard to independent
404 components of the Lab color space (Fig 4D). Interestingly, the selected pool deviated
405 significantly from the full population with regard to both the mean and variance for each
406 of the three Lab color components (Fig 4D). Comparative plots of mean Lab space for
407 the total population (in gray) and selected pool (in red) clearly show that the source of
408 divergence between these two populations comes from an accentuated bimodal
409 distribution on either end of the spectra within the selected pool, indicating that the
410 breeder is selecting along the extremes of the color space. For example, within the L
411 spectrum (the light-to-dark spectrum), the enriched bimodal distribution, reflects strong
412 selection for both bright and dark (deep colored) pixel values (p-value for mean L =
413 $7.99e-06$; Fig 4D). Furthermore, our analysis revealed significant divergence in the
414 distribution of selected versus total population values for variance within the Lab space
415 (p-values for L= $1.15e-45$, a= $2.16e-187$, b= $2.48e-44$). Again, graphs for the selected pool
416 have strong bimodal distributions for all three Lab spectra indicating that there was
417 selection for varieties with either high color contrast or uniform (solid color) patterning
418 (Fig 4D). In contrast, the total population graphs are concentrated around a single mean
419 peak (Fig 4D). Taken together, this analysis demonstrates how the “breeder’s eye”
420 reshaped the selected pool to significantly enhance mirror symmetry for both color and
421 shape, and concentrate the cultivars with either high color contrast or complete color
422 uniformity. Notably, this analysis accounts for the first round of selection where a high
423 level of variability concentrated around both commercial targets and novel aesthetic
424 traits are maintained. Approximately 6-8 of the plants from this large selection pool are
425 taken through the commercialization process.

426

427 **Public survey shows strong overlap between public preferences and breeder**
428 **selection**

429
430 Once we established the quantitative color structure for our breeding population, we
431 explored how the existing coleus color space matched with public color preferences. To
432 do this, we created a pilot survey that was openly distributed using a dedicated Twitter
433 account (@ColeusColours). To avoid the confounding influence of leaf shape on color
434 preference, we standardized the leaf orientation based on the bilateral symmetrical line
435 and deformed our leaf shapes into circles using a thin plate spline interpolation (Fig 5A),
436 this method smoothly transforms the border shape into a uniform edge with minor
437 distortion of the internal color patterning. Next, we performed a principal component
438 analysis with our circularized leaves (Fig 5B-C) and used the top principal components
439 to construct our survey for color preference. Our survey presented 8 questions that
440 asked the participants to select their preference from the mean and plus or minus a few
441 standard deviations along PC axis (“eigencolors”) for each of the top 8 principal
442 components (Fig 5D). We gathered data from 172 participants, plotted each of their
443 preferences (Fig 5E), and then reconstructed the ideal leaf based on public preferences
444 for the first eight eigencolors with weighted contributions based on the percent variance
445 contained within each PC (Fig 5F). Our results show that participants have a strong
446 preference for very green (responses to PC1 in Fig 5E), very magenta (responses to
447 PC2 in Fig 5E), and leaves with either high contrast color patterns (responses to the
448 contrasting standard deviation extremes in PC3-PC8). The resulting ideal leaf that was
449 reconstructed from the survey data has a high contrast bright green border with internal
450 magenta pigmentation and yellow base (Fig 5F). This ideal leaf not only matches an
451 existing variegated pattern that was resolved in the lower left hand quadrant of MD 3
452 and MD 4 in our original population analysis (Fig 2H), it is also consistent with the
453 direction of breeding in our selected pool (Fig 4D). This result indicates that even with
454 this small pilot survey, there is strong overlap between public preferences and new
455 cultivar development.

456
457 **Discussion**

458
459 High-throughput phenotyping (HTP) has transformed our ability to select and optimize
460 plant traits (Das *et al.*, 2015; Shakoor *et al.*, 2017; York, 2019; Liu *et al.*, 2020) .
461 Relative to morphological and architectural phenotypes, approaches for collecting and
462 analyzing color patterns in plants remain limited. Indeed, existing methods of HTP data
463 analysis are not well-suited for the large suite of patterning phenotypes exhibited in
464 ornamental plants, like Coleus. In this paper, we utilize a new approach to address the
465 problem of complex color patterning in a large Coleus breeding population. We
466 partitioned the 2-dimensional leaf into different zones based on morphology and
467 transformed the color data into a continuous, three-dimensional color space, and
468 applied a Gaussian density estimator to extract pixel patterning across space. Using this
469 approach we were able to successfully resolve the major pigmentation patterns
470 contained within one of the largest and most diverse color patterned breeding
471 populations in the world. Historically, these patterns were discussed using qualitative
472 descriptors. By extracting the quantitative features underlying this pattern space, we
473 were able to mathematically analyze relationships between maternal plants and their
474 progeny, identify how aesthetic preferences reshape the color properties of the breeding
475 population, and independently address whether public preferences align with
476 commercial breeding goals.

477
478 Our maternal-offspring color analysis may be one of the first times that the inheritance
479 of pigmentation traits has been analyzed through this quantitative lens. We identified
480 quantitative connections between color variance in maternal plants and their offspring
481 that have direct applications for ornamental breeding. For example, breeders looking to
482 increase the range of brightness within their population can start with a brighter parental
483 population; we show that brighter mothers produce offspring that express a wider
484 variance of brightness. Those aiming to increase overall color variation would want to
485 start with parental plants that exhibit complex color patterning, as these mothers
486 produced offspring with the largest variance in terms of pixel complexity. In line with
487 classic genetic studies for coleus that identified purple as a dominant trait and green
488 and yellow as recessive, we found that mothers with pixel concentrations on the green

489 and yellow ends of the spectrum produced offspring that had wider color variation. In
490 essence, recessive color palettes could be considered blank canvases for breeding new
491 pattern variants.

492
493 Our analysis of features associated with breeder selection supports long-held theories
494 about aesthetic preferences in humans; aesthetic preference for bilateral symmetry
495 (Birkhoff, 1933) is reflected in the breeding process, where we identified significant
496 enrichment for bilateral color and shape symmetry. Moreover, we found that public
497 preferences for leaves with high color contrast largely agrees with the independent
498 selection process for breeding new cultivars. As mentioned previously, new coleus
499 cultivars are currently sight-selected through a process that involves extensive
500 screening by professional and amateur breeders. The strong quantitative agreement
501 between well-established aesthetic preferences and the breeding process, opens the
502 possibility for automating this first step of cultivar selection. It is not hard to imagine
503 taking this a step further, transforming the cultivar selection process into a customized
504 system. Simple surveys, like the Coleus Colours pilot survey conducted for this study,
505 could help people identify their ideal patterns and automated population screening
506 would match a novel cultivar from the breeding population with the customer. This
507 reimagined breeding approach offers people the personalized experience of designing
508 and naming their own, unique coleus cultivar.

509
510 Pigmentation patterns have fascinated scientists for centuries. These visual cues direct
511 plant-pollinator interactions (Leonard & Papaj, 2011; Whitney *et al.*, 2013), fend off
512 herbivores (Lev-Yadun, 2017), and as shown in this study, influence aesthetic value in
513 ornamentals. A simple, yet elegant model involving a reaction-diffusion based
514 mechanism, was famously put forth by Alan Turing to explain the diversity of pattern
515 formation in nature (Turing, 1953). Recent work in the genus *Mimulus* uncovered
516 genetic regulators that fit this Turing-based model, and direct the patterning of nectar
517 guides through a reaction-diffusion interaction between an activator (NEGAN) and its
518 inhibitor (RTO) (Ding *et al.*, 2020). Beyond this specific result, significant progress
519 towards mapping the underlying genetic mechanisms that regulate pigment deposition

520 has been made using diverse floral models. In these systems, an R2R3 Myb, bHLH,
521 and WDR “MBW” transcriptional regulon has been identified as a central regulator for
522 color patterning, controlling both orange carotenoid and purple/red anthocyanin
523 deposition ([Sagawa et al. 2016](#); [Ludwig et al. 1989](#); [Albert et al. 2014](#)). In contrast to
524 floral systems, relatively little is known about the genetics of color patterning in
525 vegetative organs; however, current knowledge including genetic mapping of
526 pigmentation variants for leaves, roots, and fruits (Albert *et al.*, 2015; Yan *et al.*, 2020;
527 Xu *et al.*, 2020; Yu *et al.*, 2020) and ectopic expression of floral regulators in vegetative
528 tissue (Albert *et al.*, 2020), indicates that the transcriptional MBW regulon is broadly
529 involved in pigmentation patterning across diverse organs.

530
531 Our coleus breeding population expresses a tremendous diversity of pattern
532 combinations. Rife and Boye (1938) recognized the potential of this prized ornamental,
533 and proposed using Coleus as a model to dissect genetic regulators for color patterning.
534 This suggestion did not get much traction, and we still know relatively little about color
535 patterning in this unique ornamental. After 80 years of stalled progress, a renewed
536 focus on the genetic regulation of pigmentation production and patterning would not
537 only advance ornamental breeding, it would push the limits of Turing’s reaction diffusion
538 model, reaching to describe the truly complex pattern variants that have drawn
539 admiration from scientists and gardeners alike.

540

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542

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550

551 **Author Contributions:**

552

553 MHF, VC, and DHC designed the imaging pipeline, DC bred the Coleus population,
554 MHF and VC collected the data, and ML developed and performed the HTP color
555 analysis. All authors contributed to writing the manuscript.

556

557 **References:**

558 **Albert NW, Butelli E, Moss SMA, Piazza P, Waite CN, Schwinn KE, Davies KM,**
559 **Martin C. 2020.** Discrete bHLH transcription factors play functionally overlapping roles
560 in pigmentation patterning in flowers of *Antirrhinum majus*. *The New phytologist*.

561 **Albert NW, Griffiths AG, Cousins GR, Verry IM, Williams WM. 2015.** Anthocyanin
562 leaf markings are regulated by a family of R2R3-MYB genes in the genus *T. trifolium*.
563 *The New phytologist* **205**: 882–893.

564 **Amézquita EJ, Quigley MY, Ophelders T, Munch E, Chitwood DH. 2020.** The shape
565 of things to come: Topological data analysis and biology, from molecules to organisms.
566 *Developmental dynamics: an official publication of the American Association of*
567 *Anatomists* **249**: 816–833.

568 **Arnal Barbedo JG. 2013.** Digital image processing techniques for detecting,
569 quantifying and classifying plant diseases. *SpringerPlus* **2**: 660.

570 **Bailey LH. 1924.** *Manual of Cultivated Plants: A Flora for the Identification of the Most*
571 *Common of the Most Common Or Significant Species of Plantsgrown in the Continental*
572 *United States and Canada for Food*. Macmillan Publ.

573 **Birkhoff GD. 1933.** *Aesthetic measure*. Cambridge, Mass.

574 **Boye CL, Rife DC. 1938.** GENETIC STUDIES OF COLEUS I. *Journal of Heredity* **29**:
575 55–60.

576 **Chitwood DH, Eithun M, Munch E, Ophelders T. 2019.** Topological Mapper for 3D
577 Volumetric Images. In: *Mathematical Morphology and Its Applications to Signal and*
578 *Image Processing*. Springer International Publishing, 84–95.

579 **Das A, Schneider H, Burrige J, Ascanio AKM, Wojciechowski T, Topp CN, Lynch**
580 **JP, Weitz JS, Bucksch A. 2015.** Digital imaging of root traits (DIRT): a high-throughput
581 computing and collaboration platform for field-based root phenomics. *Plant methods* **11**:
582 51.

583 **Ding B, Patterson EL, Holalu SV, Li J, Johnson GA, Stanley LE, Greenlee AB,**
584 **Peng F, Bradshaw HD Jr, Blinov ML, et al. 2020.** Two MYB Proteins in a Self-

- 585 Organizing Activator-Inhibitor System Produce Spotted Pigmentation Patterns. *Current*
586 *biology: CB* **30**: 802–814.e8.
- 587 **Fahlgren N, Gehan MA, Baxter I. 2015.** Lights, camera, action: high-throughput plant
588 phenotyping is ready for a close-up. *Current opinion in plant biology* **24**: 93–99.
- 589 **Fasoula DA, Ioannides IM, Omirou M. 2019.** Phenotyping and Plant Breeding:
590 Overcoming the Barriers. *Frontiers in plant science* **10**: 1713.
- 591 **Frank MH, Chitwood DH. 2016.** Plant chimeras: The good, the bad, and the ‘Bizzaria’.
592 *Developmental biology* **419**: 41–53.
- 593 **Gehan MA, Fahlgren N, Abbasi A, Berry JC, Callen ST, Chavez L, Doust AN,**
594 **Feldman MJ, Gilbert KB, Hodge JG, et al. 2017.** PlantCV v2: Image analysis software
595 for high-throughput plant phenotyping. *PeerJ* **5**: e4088.
- 596 **Gehan MA, Kellogg EA. 2017.** High-throughput phenotyping. *American journal of*
597 *botany* **104**: 505–508.
- 598 **Gobalakrishnan N, Pradeep K, Raman CJ, Javid Ali L, Gopinath MP. 2020.** A
599 Systematic Review on Image Processing and Machine Learning Techniques for
600 Detecting Plant Diseases. *2020 International Conference on Communication and Signal*
601 *Processing (ICCSP)*.
- 602 **Hsu C-C, Chen Y-Y, Tsai W-C, Chen W-H, Chen H-H. 2015.** Three R2R3-MYB
603 transcription factors regulate distinct floral pigmentation patterning in *Phalaenopsis* spp.
604 *Plant physiology* **168**: 175–191.
- 605 **Ibba MI, Crossa J, Montesinos-López OA, Montesinos-López A, Juliana P,**
606 **Guzman C, Delorean E, Dreisigacker S, Poland J. 2020.** Genome-based prediction of
607 multiple wheat quality traits in multiple years. *The plant genome* **11**: 3.
- 608 **Leonard AS, Papaj DR. 2011.** ‘X’ marks the spot: The possible benefits of nectar
609 guides to bees and plants: Nectar guides and bumblebee foraging. *Functional ecology*
610 **25**: 1293–1301.
- 611 **Lev-Yadun S. 2017.** Defensive animal and animal-action mimicry by plants. *Israel*
612 *Journal of Plant Sciences*: 1–31.
- 613 **Li B-J, Zheng B-Q, Wang J-Y, Tsai W-C, Lu H-C, Zou L-H, Wan X, Zhang D-Y, Qiao**
614 **H-J, Liu Z-J, et al. 2020b.** New insight into the molecular mechanism of colour
615 differentiation among floral segments in orchids. *Communications biology* **3**: 89.
- 616 **Li M, An H, Angelovici R, Bagaza C, Batushansky A, Clark L, Coneva V, Donoghue**
617 **MJ, Edwards E, Fajardo D, et al. 2018a.** Topological Data Analysis as a Morphometric
618 Method: Using Persistent Homology to Demarcate a Leaf Morphospace. *Frontiers in*
619 *plant science* **9**: 553.

- 620 **Li M, Frank MH, Coneva V, Mio W, Chitwood DH, Topp CN. 2018b.** The Persistent
621 Homology Mathematical Framework Provides Enhanced Genotype-to-Phenotype
622 Associations for Plant Morphology. *Plant physiology* **177**: 1382–1395.
- 623 **Li M, Frank MH, Migicovsky Z. 2019a.** ColourQuant: a high-throughput technique to
624 extract and quantify colour phenotypes from plant images. *arXiv [q-bio.QM]*.
- 625 **Li M, Klein LL, Duncan KE, Jiang N, Chitwood DH, Londo JP, Miller AJ, Topp CN.**
626 **2019b.** Characterizing 3D inflorescence architecture in grapevine using X-ray imaging
627 and advanced morphometrics: implications for understanding cluster density. *Journal of*
628 *experimental botany* **70**: 6261–6276.
- 629 **Li M, Shao M-R, Zeng D, Ju T, Kellogg EA, Topp CN. 2020a.** Comprehensive 3D
630 phenotyping reveals continuous morphological variation across genetically diverse
631 sorghum inflorescences. *The New phytologist* **226**: 1873–1885.
- 632 **Lin-Wang K, Bolitho K, Grafton K, Kortstee A, Karunairetnam S, McGhie TK,**
633 **Espley RV, Hellens RP, Allan AC. 2010.** An R2R3 MYB transcription factor associated
634 with regulation of the anthocyanin biosynthetic pathway in Rosaceae. *BMC plant biology*
635 **10**: 50.
- 636 **Liu S, Barrow C, Hanlon MT, Lynch J, Bucksch A. 2020.** DIRT/3D: 3D phenotyping
637 for maize (*Zea mays*) root architecture in the field. *bioRxiv*.
- 638 **Mutka AM, Bart RS. 2014.** Image-based phenotyping of plant disease symptoms.
639 *Frontiers in plant science* **5**: 734.
- 640 **Paton A, Mwanyambo M, Culham A. 2018.** Phylogenetic study of *Plectranthus* ,
641 *Coleus* and allies (Lamiaceae): taxonomy, distribution and medicinal use. *Botanical*
642 *journal of the Linnean Society. Linnean Society of London* **188**: 355–376.
- 643 **Paton AJ, Mwanyambo M, Govaerts RHA, Smitha K, Suddee S, Phillipson PB,**
644 **Wilson TC, Forster PI, Culham A. 2019.** Nomenclatural changes in *Coleus* and
645 *Plectranthus* (Lamiaceae): a tale of more than two genera. *PhytoKeys* **129**: 1–158.
- 646 **Pedley R, Pedley K. 1974.** *Coleus: A guide to cultivation and identification*. J.
647 Bartholomew.
- 648 **Prunet N, Duncan K. 2020.** Imaging flowers: a guide to current microscopy and
649 tomography techniques to study flower development. *Journal of experimental botany*
650 **71**: 2898–2909.
- 651 **Rife DC. 1948.** SIMPLY INHERITED VARIATIONS IN COLEUS: A Résumé. *The*
652 *Journal of heredity* **39**: 85–91.
- 653 **Rogers R. 2008.** *Coleus: Rainbow foliage for containers and gardens*. Timber Press
654 (OR).

- 655 **Sagawa JM, Stanley LE, LaFountain AM, Frank HA, Liu C, Yuan Y-W. 2016.** An
656 R2R3-MYB transcription factor regulates carotenoid pigmentation in *Mimulus lewisii*
657 flowers. *The New phytologist* **209**: 1049–1057.
- 658 **Shakoor N, Agnew E, Ziegler G, Lee S, Lizárraga C, Fahlgren N, Baxter I, Mockler**
659 **TC. 2019.** Genomewide association study reveals transient loci underlying the genetic
660 architecture of biomass accumulation under cold stress in Sorghum. *Cold Spring Harbor*
661 *Laboratory*: 760025.
- 662 **Shakoor N, Lee S, Mockler TC. 2017.** High throughput phenotyping to accelerate crop
663 breeding and monitoring of diseases in the field. *Current opinion in plant biology* **38**:
664 184–192.
- 665 **Singh D, Wang X, Kumar U, Gao L, Noor M, Imtiaz M, Singh RP, Poland J. 2019.**
666 High-Throughput Phenotyping Enabled Genetic Dissection of Crop Lodging in Wheat.
667 *Frontiers in plant science* **10**: 394.
- 668 **Stanley LE, Ding B, Sun W, Mou F, Hill C, Chen S, Yuan Y-W.** A Tetratricopeptide
669 Repeat Protein Regulates Carotenoid Biosynthesis and Chromoplast Development in
670 Monkeyflowers (*Mimulus*).
- 671 **Suddee S, A. J. Paton, Parnell JAN. 2004.** A Taxonomic Revision of Tribe Ocimeae
672 Dumort. (Lamiaceae) in Continental South East Asia II. Plectranthinae. *Kew bulletin /*
673 *Royal Botanic Gardens* **59**: 379–414.
- 674 **Tilney-Bassett RAE, Others. 1986.** *Plant chimeras*. Edward Arnold (Publishers) Ltd.
- 675 **Turing AM. 1953.** The chemical basis of morphogenesis. 1953. *Bulletin of*
676 *mathematical biology* **52**: 153–97; discussion 119–52.
- 677 **Underhill AN, Hirsch CD, Clark MD. 2020.** Evaluating and Mapping Grape Color Using
678 Image-Based Phenotyping. *Plant Phenomics* **2020**.
- 679 **Vanhees DJ, Loades KW, Bengough AG, Mooney SJ, Lynch JP. 2020.** Root
680 anatomical traits contribute to deeper rooting of maize under compacted field
681 conditions. *Journal of experimental botany* **71**: 4243–4257.
- 682 **Whitney HM, Milne G, Rands SA, Vignolini S, Martin C, Glover BJ. 2013.** The
683 influence of pigmentation patterning on bumblebee foraging from flowers of *Antirrhinum*
684 *majus*. *Naturwissenschaften* **100**: 249–256.
- 685 **Xie X, Ma Y, Liu B, He J, Li S, Wang H. 2020.** A Deep-Learning-Based Real-Time
686 Detector for Grape Leaf Diseases Using Improved Convolutional Neural Networks.
687 *Frontiers in plant science* **11**: 751.
- 688 **Xu Z-S, Yang Q-Q, Feng K, Yu X, Xiong A-S. 2020.** DcMYB113, a root-specific R2R3-
689 MYB, conditions anthocyanin biosynthesis and modification in carrot. *Plant*
690 *biotechnology journal* **18**: 1585–1597.

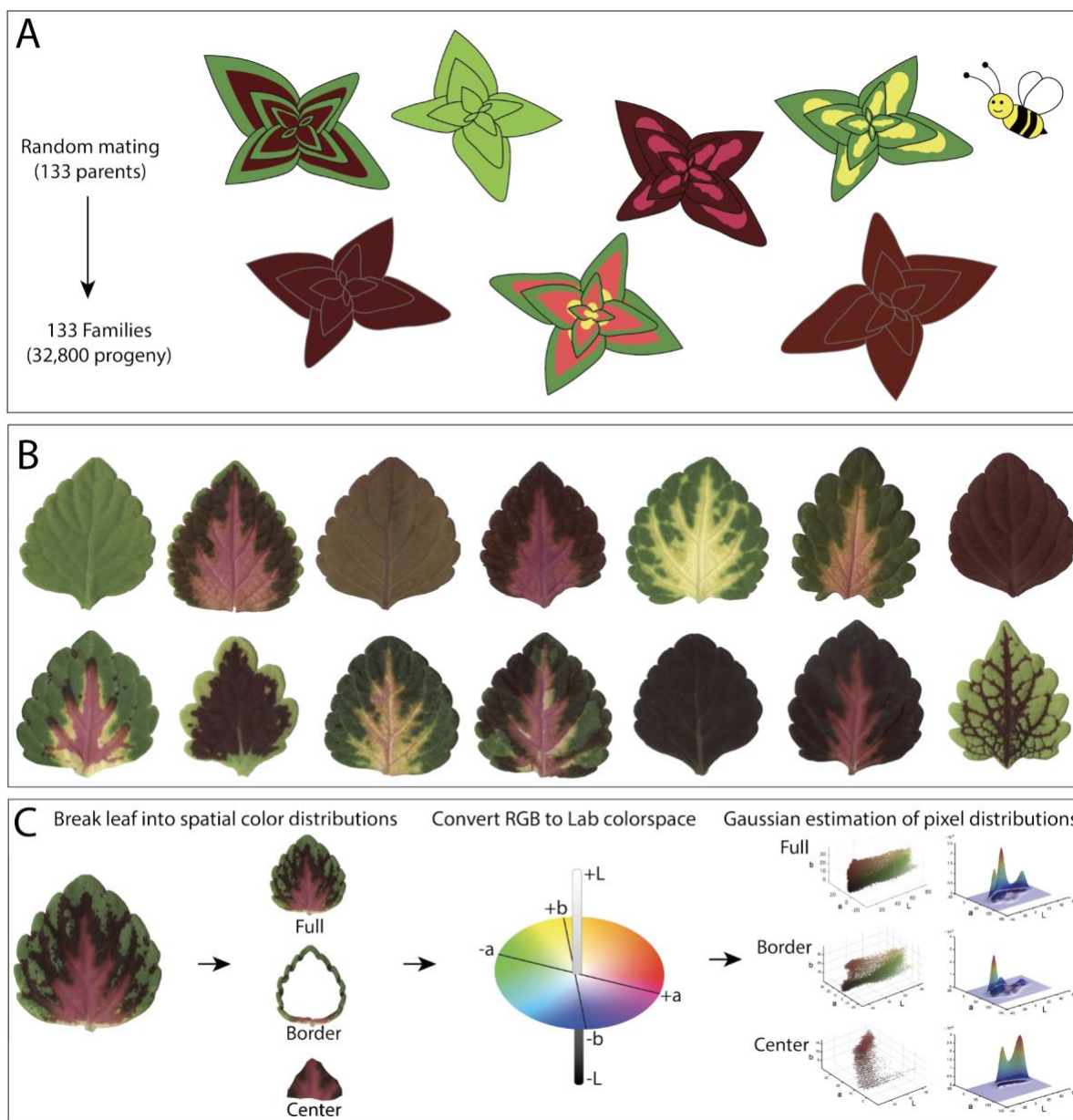
- 691 **Yamagishi M, Shimoyamada Y, Nakatsuka T, Masuda K. 2010.** Two R2R3-MYB
692 Genes, Homologs of Petunia AN2, Regulate Anthocyanin Biosyntheses in Flower
693 Tepals, Tepal Spots and Leaves of Asiatic Hybrid Lily. *Plant and Cell Physiology* **51**:
694 463–474.
- 695 **Yan S, Chen N, Huang Z, Li D, Zhi J, Yu B, Liu X, Cao B, Qiu Z. 2020.** Anthocyanin
696 Fruit encodes an R2R3-MYB transcription factor, SIAN2-like, activating the transcription
697 of SIMYBATV to fine-tune anthocyanin content in tomato fruit. *The New phytologist* **225**:
698 2048–2063.
- 699 **York LM. 2019.** Functional phenomics: an emerging field integrating high-throughput
700 phenotyping, physiology, and bioinformatics. *Journal of experimental botany* **70**: 379–
701 386.
- 702 **Yu X, Qin Q, Wu X, Li D, Yang S. 2020.** Genetic and Physical Localization of the Gene
703 Controlling Leaf Pigmentation Pattern in *Medicago truncatula*. *G3* **10**: 4159–4165.
- 704 **Zheng X, Om K, Stanton KA, Thomas D, Cheng PA. 2020.** MYB5a/NEGAN activates
705 petal anthocyanin pigmentation and shapes the MBW regulatory network in *Mimulus*
706 *luteus* var. *variegatus*. *bioRxiv*.

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708 **Figures and legends**

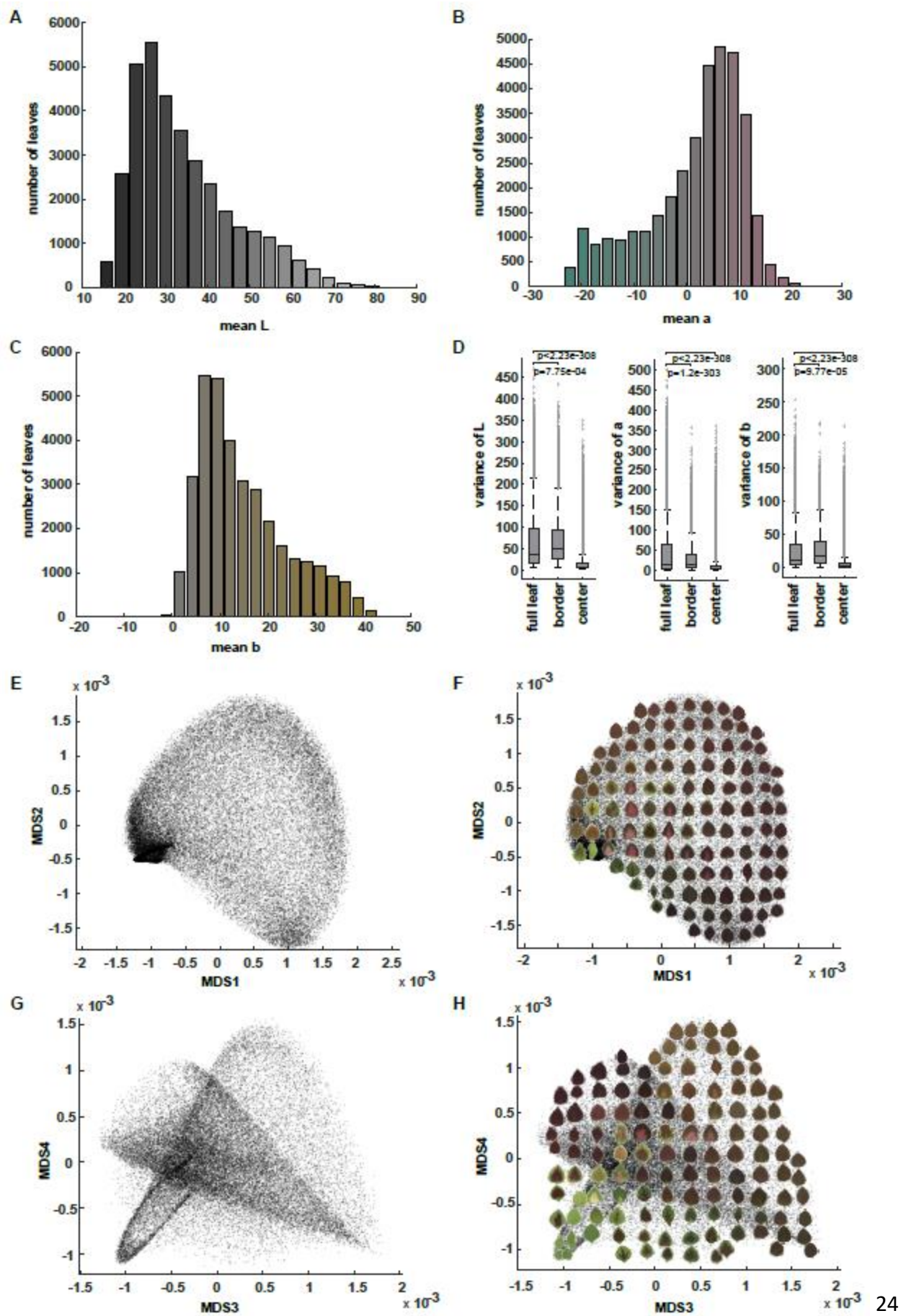
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710 **Figure 1: Experimental design, high throughput sampling, and color analysis.** (A)
711 133 field-grown parents were randomly mated by pollinators, seeds were collected from
712 each maternal plant, sown in progeny family blocks and grown for 5-6 weeks in a
713 greenhouse; (B) One fully-expanded leaf was harvested and scanned from each plant in
714 the population; (C) Color thresholding was used to isolate binary masks for each leaf.
715 Discrete RGB color matrices were converted to the continuous Lab color space, and
716 color matrices for each leaf were spatially separated into segments: “full” – defined as
717 the entire color matrix, “border” – defined as the outer 15% of pixels from the leaf
718 boundary to the centroid, and “center” – defined as the inner 75% of pixels from the
719 centroid to the boundary. A Gaussian density estimator was used to extract quantitative
720 pigmentation data (only 2D Gaussian density estimator was shown for visualization).

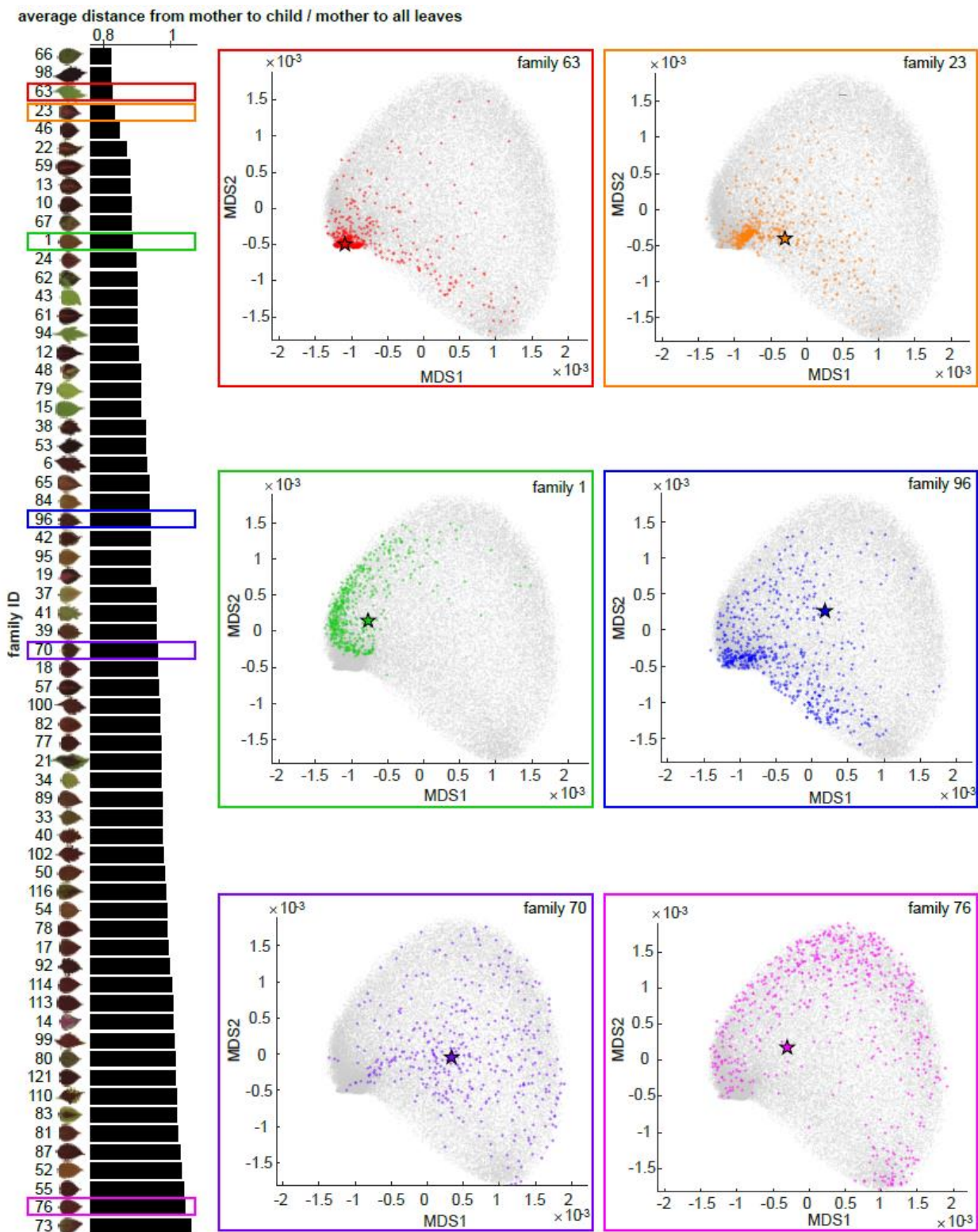


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725 **Figure 2: CIELAB (L*a*b*) color distribution.** (A) The histogram of mean L (lightness)
726 values of the studied coleus population. The color for each bar corresponds to the Lab
727 color with L value at x axis, a=0 and b=0; (B) Histogram of mean a (green to magenta)
728 values. The color for each bar corresponds to the Lab color with a value at x axis, L=50
729 and b=0; (C) Histogram of mean b (blue to yellow) values. The color for each bar
730 corresponds to the Lab color with b value at x axis, L=50 and a=0; (D) Boxplot of the
731 variance of L, a, and b for full leaf, border, and center. The “+” signs mark outliers that
732 are more than 1.5 interquartile ranges above the upper quartile or below the lower
733 quartile for each box, the central line indicates the median, top and bottom edges of the

734 box indicate 25th and 75th percentiles. Whiskers extend to the most extreme non-
735 outliers of the data. P-values for full leaf versus border, full leaf versus center are also
736 shown using paired sample t-test; **(E)** and **(G)** Multidimensional scaling (MDS) plot
737 (MDS1 vs MDS2 in (E) and MDS3 vs MDS4 in (G)) for the pattern difference defined by
738 the difference of Gaussian density estimator in 3D Lab colorspace across full leaf,
739 border and center; **(F)** and **(H)** The same MDS plots shown in (E) and (G) but with
740 example leaves superimposed to provide visual examples of the data distribution.
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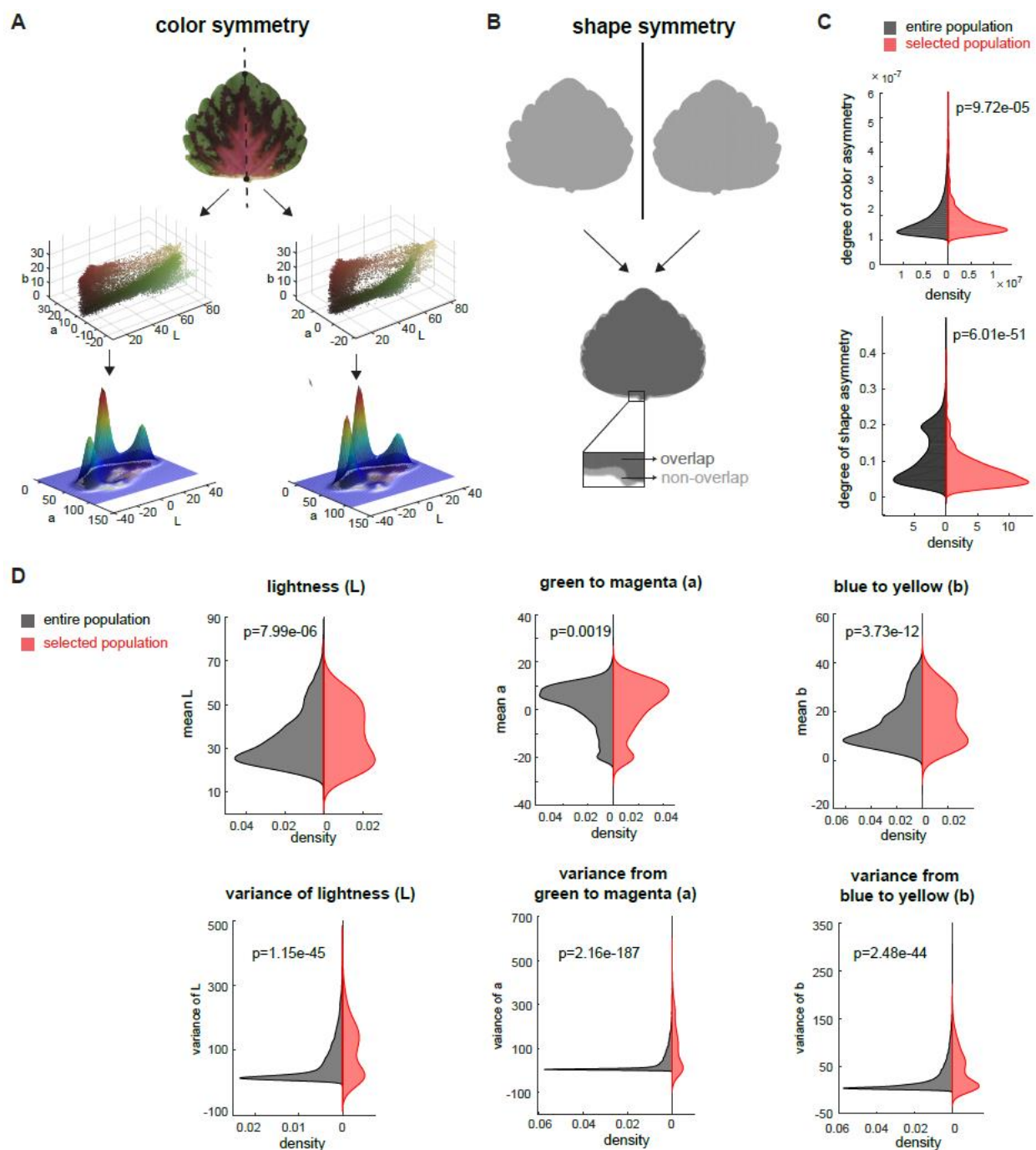
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744 **Figure 3: Maternal Plant-Progeny relationships.** On the left panel, each bar shows
745 the average distance from maternal plants to progeny divided by the average distance
746 from maternal plants to all leaves (x-axis) for each progeny family (y-axis)
747 superimposed upon the scan of the maternal plant. On the right panels, there are six
748 MDS plots (MDS1 vs MDS2) from six progeny families as examples with different colors
749 correspond to the families highlighted in the same colored rectangles on the left panel.
750 On each MDS plot, grey dots show all leaves, colored stars represent the maternal
751 plants, and colored dots are the progeny.



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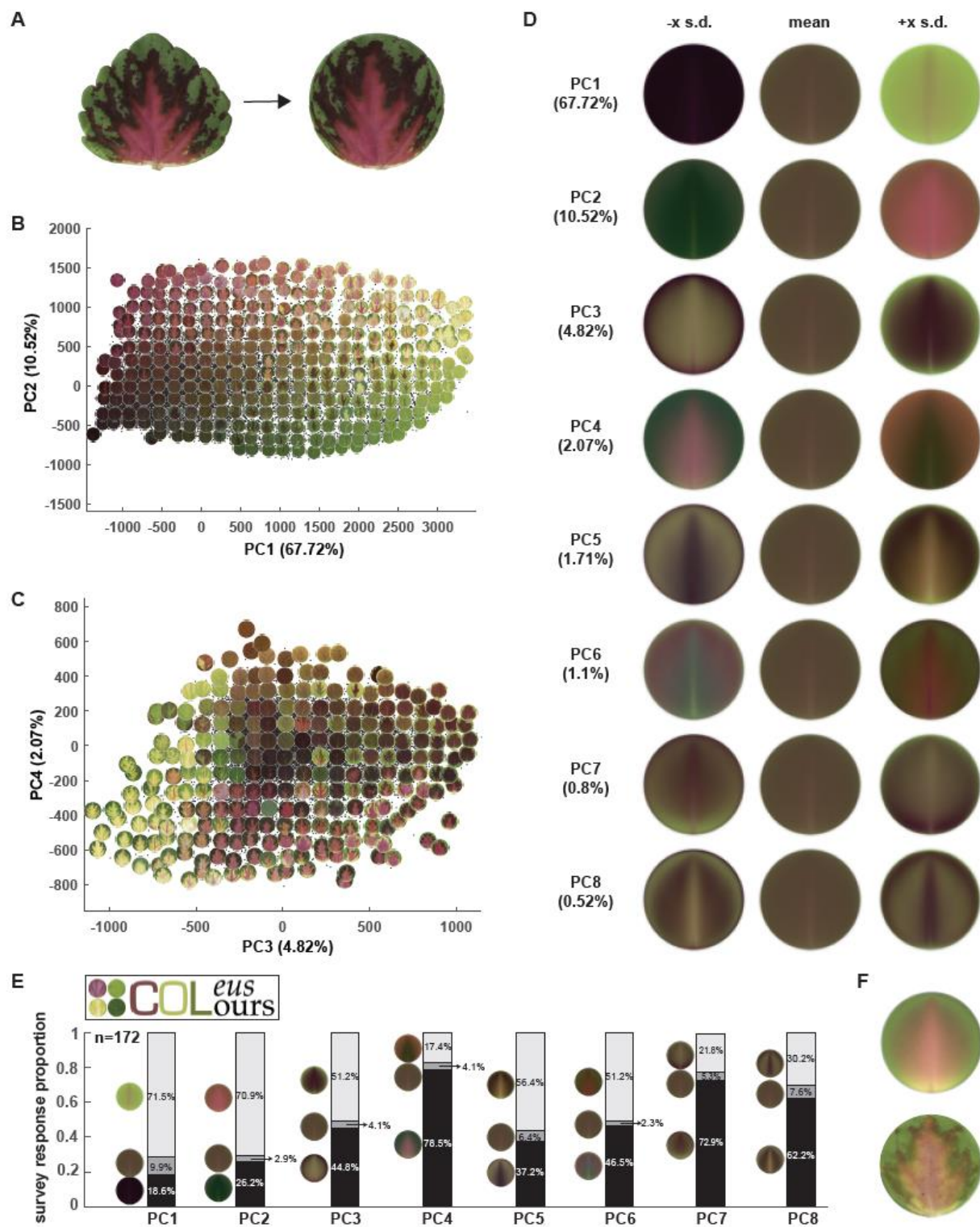
757 **Figure 4: Influence of color and shape on cultivar selection.**

758 **(A)** Mirror symmetry of color: Partitioning of each leaf into left and right halves (top
759 panel), convert each part into 3D point cloud in Lab color space (middle panel), and
760 calculate the 3D Gaussian density estimator (lower panel, only shows 2D Gaussian
761 density estimator for visualization); **(B)** Mirror symmetry of shape: flip the leaf
762 horizontally (top panel), measure the non-overlapped area (lower panel) and calculate
763 the percentage of non-overlapped area over the leaf area; **(C)** Distribution of degree of
764 color asymmetry (top panel) and shape asymmetry (bottom panel) for entire population
765 (in black) and selected population (in red); **(D)** Distribution of mean L (top left), mean a
766 (top middle), mean b (top right), variance of L (bottom left), variance of a (bottom
767 middle), and variance of b (bottom right) for entire population (in black) and selected
768 population (in red). Significance was measured using a two sample t-test for uneven
769 sample sizes.



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780 **Figure 5: Public survey for color preferences using shape-transformed leaves. (A)**
781 Deform each leaflet into a disk by thin plate spline interpolation – non-linear deformation
782 into a unit circle; **(B)** and **(C)** Principal component analysis plot superimposed upon
783 some example of leaves (PC1 vs PC2 in (B) and PC3 vs PC4 in (C)) for the pixel Lab
784 values of deformed leaflet; **(D)** Eigencolors for the first eight PCs and the percentage of
785 variance they explained. For PC k, the eigencolor at -x SD and +x SD along PC axis are
786 shown, where $x=3+(k-1)*0.5$ for better visualization; **(E)** Survey logo (top left) and the
787 survey result from 172 responses; **(F)** Reconstructed pattern (top) and closest real leaf
788 (bottom) from first eight eigencolors with weights guided by the survey response
789 proportion.
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Supplemental Figures

797 **Figure S1: Data collection. (A)** Data were collected for one leaf from the first fully
798 expanded leaf pair. **(B)** Leaves were imaged on a flatbed scanner with a color card for
799 color correction and a ruler.
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A - leaf selection

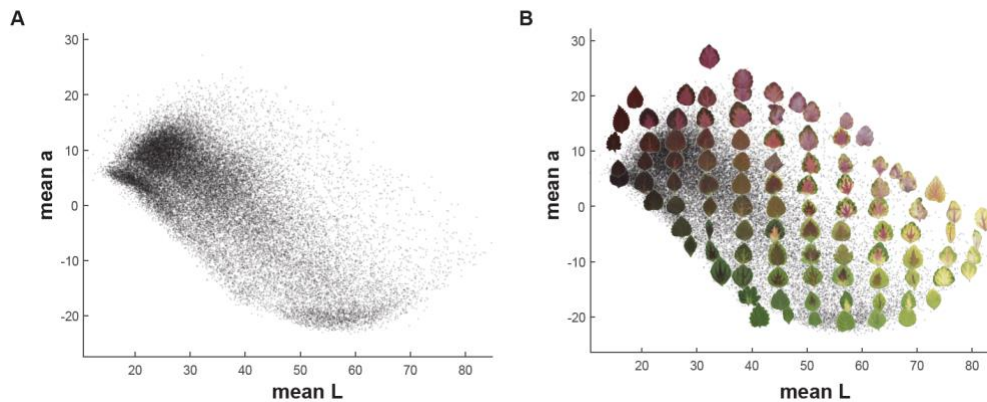


B - leaf scanning



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Figure S2: Color distribution for mean L and mean a. Plot of mean L (x-axis) and a
(y-axis) for the full coleus population with point density (A) and example leaves overlaid
on top of points (B).

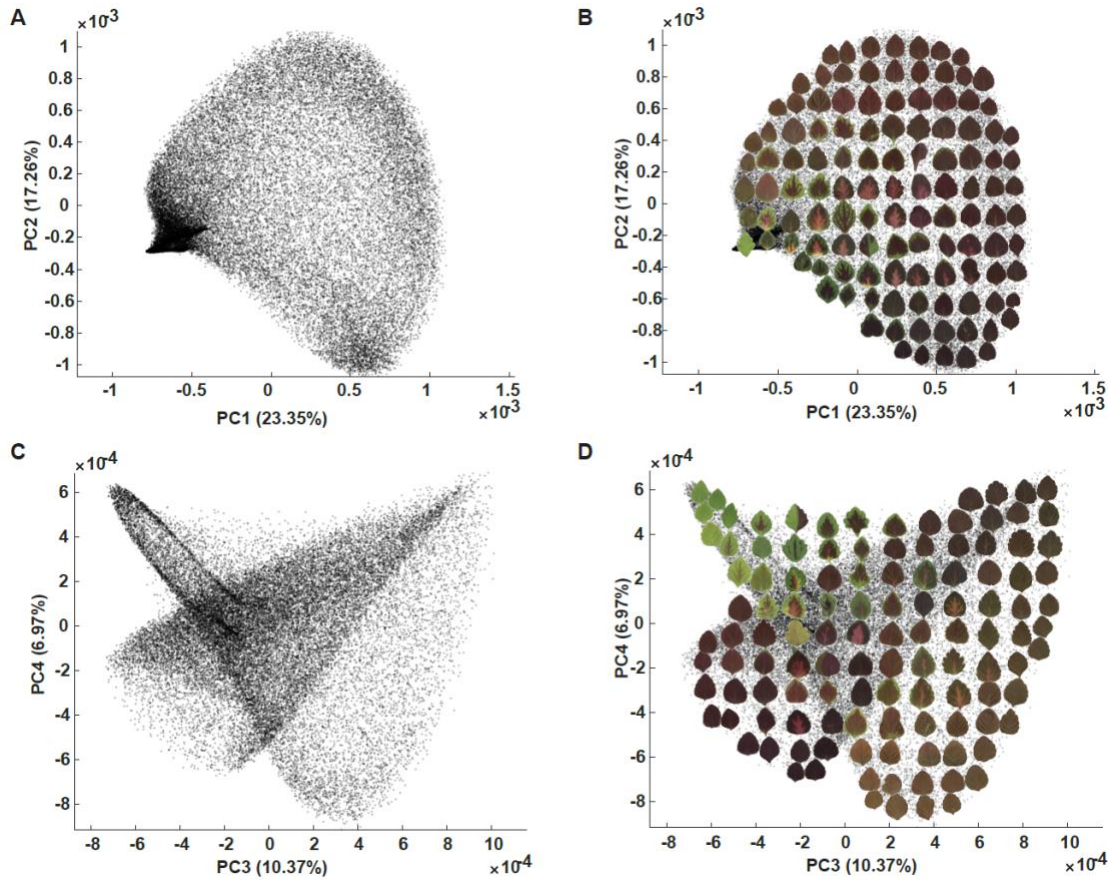


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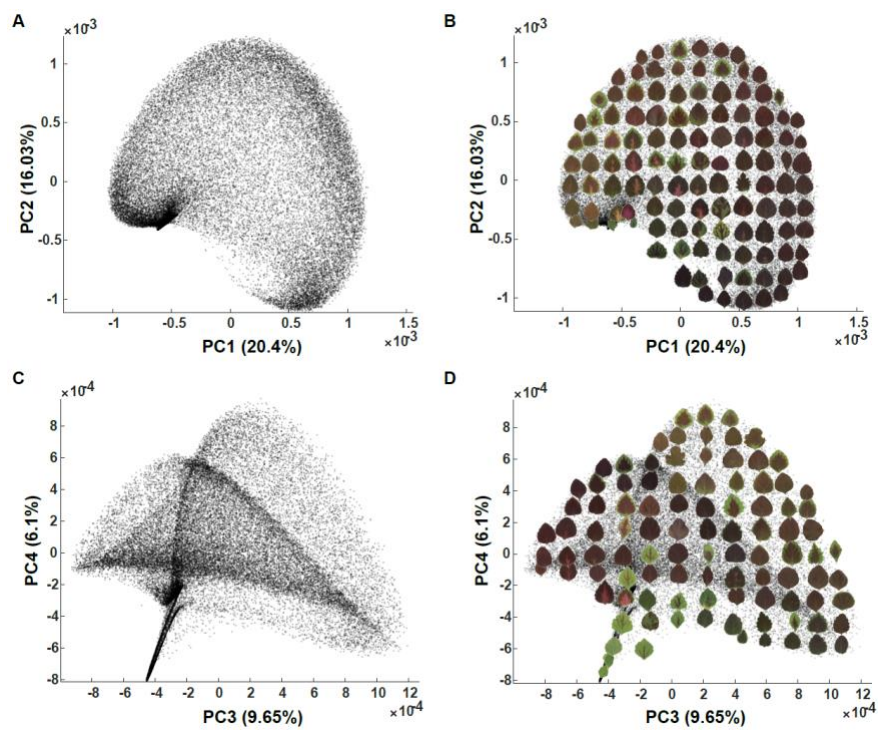
Figure S3: Principal Component Analysis for color in the entire coleus population using segmented or full leaf data sampling. PCA plots for Lab Gaussian density of color distribution with example leaves overlaid on top of data points for the full leaf (A), leaf border (B), and leaf center (C).

A: Lab Gaussian density color distribution for full leaf



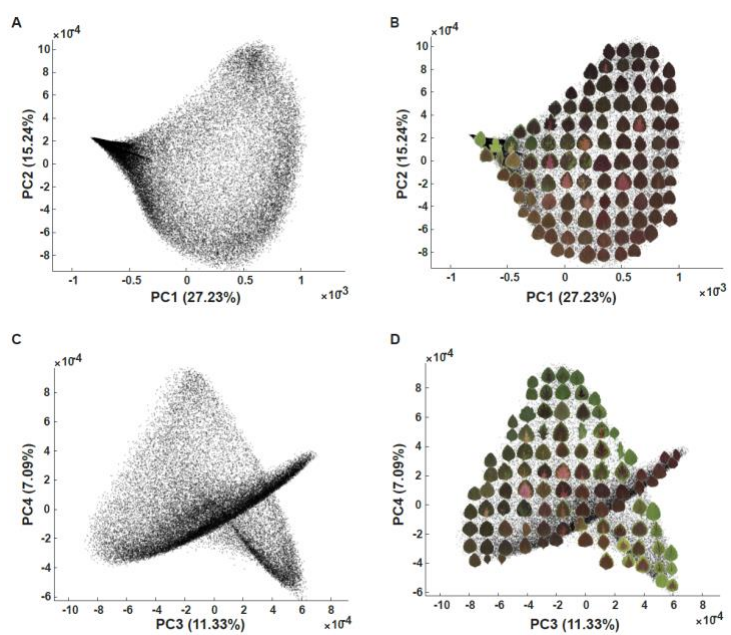
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B: Lab Gaussian density color distribution for leaf border



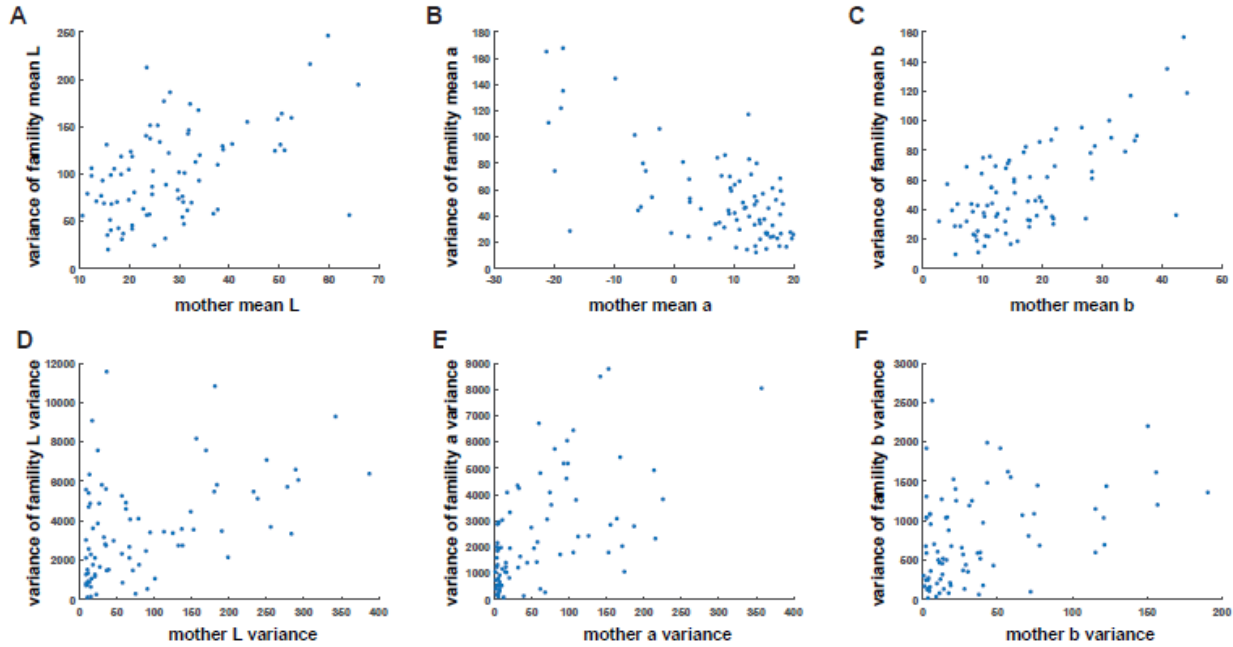
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C: Lab Gaussian density color distribution for center



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860 **Figure S4: Maternal Plant-Progeny relationships based on mean and variance of**
861 **Lab color.** Scatter plots with x-axis represents the mean L (A), mean a (B), and mean b
862 (C) of maternal plant and y-axis represents the variance of the corresponding mean
863 value of the progeny, respectively; Scatter plots with x-axis represents the variance of L
864 (D), variance of a (E), and variance of b (F) of maternal plant and y-axis represents the
865 variance of the corresponding variance value of the progeny, respectively.



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