

# Natural variation in stomata size contributes to the local adaptation of water-use efficiency in *Arabidopsis thaliana*

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## Abstract

Stomata control gas exchanges between the plant and the atmosphere. How natural variation in stomata size and density contributes to resolve trade-offs between carbon uptake and water-loss in response to local climatic variation is not yet understood. We developed an automated confocal microscopy approach to characterize natural genetic variation in stomatal patterning in 330 fully-sequenced *Arabidopsis thaliana* ecotypes collected throughout the European range of the species. We compared this to variation in water-use efficiency, measured as carbon isotope discrimination ( $\delta^{13}\text{C}$ ). Combined with public genomic and environmental resources, we show that genetic variation for stomata size and density is pervasive in *Arabidopsis thaliana*. A positive correlation between stomata size and  $\delta^{13}\text{C}$  further shows that this variation has consequences on water-use efficiency. Genome-wide association analyses reveal that many loci of small effect contribute not only to variation in stomata patterning but also to its co-variation with carbon uptake parameters. Yet, we report two novel QTL affecting  $\delta^{13}\text{C}$  independently of stomata patterning. This suggests that, in *A. thaliana*, both morphological and physiological variants contribute to genetic variance in water-use efficiency. Patterns of regional differentiation and co-variation with climatic parameters indicate that natural selection has contributed to shape some of this variation, especially in Southern Sweden, where water availability is comparatively more limited in Spring.

## Keywords

GWAS; stomata; water-use efficiency; *Arabidopsis thaliana*;  $Q_{ST}$   $F_{ST}$  analysis; local adaptation to climate

## 1 Introduction

2 Stomata form microscopic pores controlling gas exchange on the surface of plant leaves.

3 These pores provide plants with a strategic lever arm to optimize the trade-off between  
4 growth and survival. As the gas exchange organ for higher plants, stomata intimately link  
5 three key functional traits: carbon (CO<sub>2</sub>) uptake, water loss and leaf cooling (Raven, 2002).

6 Therefore, the density, distribution and regulation of stomata, may have played a pivotal role  
7 in shaping the diversity of plant communities throughout the globe (Lambers, Chapin, &  
8 Pons, 1998; McDowell et al., 2008).

9 Short term plastic changes in rate of gas exchange (termed stomatal conductance) provide a  
10 first level at which the plant manages the conflicting demands on carbon uptake and water  
11 loss in the face of daily fluctuations in water and light availability. For this, the two guard  
12 cells that form the stomata modulate conductance by modifying their turgor in response to  
13 environmental and internal signals (Chater et al., 2011; Kinoshita et al., 2011). This ensures,  
14 for example, that plants do not desiccate at high noon when water evaporation is maximal or  
15 at night when photosynthesis is not active (Daszkowska-Golec & Szarejko, 2013).

16 Less well understood, however, is how variation in the arrangement and size of stomata on  
17 the leaf surface (stomatal patterns) participates in the resolution of the conflict between water  
18 loss and growth. Physical conductance theory predicts that small stomata in high density are  
19 required to maximize conductance (Franks & Beerling, 2009). Experimental data, however,  
20 do not always support this prediction. A significant relationship between stomatal patterns  
21 and conductance has sometimes been reported (Anderson & Briske, 1990; Carlson, Adams, &  
22 Holsinger, 2016; Franks & Beerling, 2009; Muchow & Sinclair, 1989; Pearce, Millard, Bray,

23 & Rood, 2006; Reich, 1984), but is not always detected (Bakker, 1991; Ohsumi, Kanemura,  
24 Homma, Horie, & Shiraiwa, 2007).

25 Much is known about the complex molecular pathway, that controls the differentiation of  
26 protodermal cells into stomata, at the expense of classical epidermal cells in the model plant  
27 species *Arabidopsis thaliana* (Bergmann & Sack, 2007; Pillitteri & Torii, 2012). Mutants in  
28 this pathway show not only modified stomata patterns, but also altered water-use efficiency  
29 (WUE), which quantifies a plant's ability to fix carbon while minimizing water loss, or  
30 survival after exposure to drought stress (Franks, W. Doheny-Adams, Britton-Harper, &  
31 Gray, 2015; Yoo et al., 2010). Thus, genetic modification of stomatal patterning can provide  
32 potentially adaptive phenotypes in more arid environments. In addition, stomatal density and  
33 size are generally strongly negatively correlated, which may either accelerate or constrain the  
34 evolution of the optimal adaptive patterns (reviewed in (Hetherington & Woodward, 2003).  
35

36 Natural variation of stomatal patterns has been evaluated in various species, showing that it  
37 often associates with increased water-use efficiency and environmental variation. In *Protea*  
38 *repens*, when measured in a common garden experiment with 19 populations, stomata density  
39 increased with annual mean temperature and decreased with summer rainfall at the source  
40 location (Carlson et al., 2016). In species of the *Mimulus guttatus* species complex grown in a  
41 common garden, accessions from drier inland populations showed decreased stomatal density  
42 associated with an increase in WUE, compared to accessions collected in humid coastal  
43 populations (Wu, Lowry, Nutter, & Willis, 2010). In *Eucalyptus globulus*, it is stomata size  
44 and not stomata density that associated with water-use efficiency. When *E. globulus*  
45 populations were grown in two field sites with contrasting rainfall, plants from the drier site  
46 had smaller stomata independent of their density and higher WUE (Franks, Drake, &

47 Beerling, 2009). This suggested that developmental correlation between stomata size and  
48 density may sometimes be alleviated to better match physiological performance with local  
49 environments.

50 Stomatal patterning also affects the efficiency of the short-term response of stomatal aperture  
51 to stress. In the *Banksia* genus, species with smaller stomata and higher densities were able to  
52 open stomata faster in response to light (Drake, Froend, & Franks, 2013). Stomatal responses  
53 are an order of magnitude slower than photosynthetic changes, and the increased time lag of  
54 larger stomata may favor water loss and reduce WUE (T. Lawson, Kramer, & Raines, 2012).

55 The plastic decrease in stomata length observed in diverse populations of *Arabidopsis lyrata*  
56 *ssp. lyrata* in response to water limitations indeed correlated with an increase in WUE  
57 (Paccard, Fruleux, & Willi, 2014). Thus, increased stomata density can, counterintuitively,  
58 contribute to improved WUE since it decreases stomata size, and in turn favors faster  
59 opening/closing reactions. Therefore, the natural variation reported for stomatal traits in  
60 various plant species, appears to have complex consequences on both physiological  
61 performance and the associations with diverse environmental factors. Yet, without an  
62 understanding of the underlying genetic architecture, the question of the adaptive relevance of  
63 stomatal patterning and its ecological drivers remains unresolved.

64 Eco-evolutionary analyses provide a powerful approach to establish the ecological importance  
65 of specific traits (Carroll, Hendry, Reznick, & Fox, 2007; Hendry, 2016). By drawing on the  
66 elaborate toolbox of population genetics and genomics, it is not only possible to test whether a  
67 given trait is genetically variable, but also to ask whether it is optimized by natural selection  
68 and to investigate the ecological determinants of the selective forces at work (Hendry, 2016;  
69 Weinig, Ewers, & Welch, 2014). In this effort, the annual species *Arabidopsis thaliana*,  
70 which thrives as a pioneer species in disturbed habitats, has a privileged position (Gaut,

71 2012). Ecotypes of *A. thaliana* show a high degree of variation in many vital phenotypic  
72 traits, which is at least partly shaped by local adaptation (Ågren & Schemske, 2012; Baxter et  
73 al., 2010; Fournier-Level et al., 2011; Postma & Ågren, 2016; Stinchcombe et al., 2004). This  
74 diversity and the availability of over 1000 fully sequenced accessions (Alonso-Blanco et al.,  
75 2016) make it an ideal species for studying ecological adaptation of plants. Indeed, genome-  
76 wide patterns of nucleotide variation can be contrasted to phenotypic variation and both the  
77 genetic architecture and the adaptive history of the traits can be reconstructed (Atwell et al.,  
78 2010; Fournier-Level et al., 2011). Eco-evolutionary approaches have allowed documenting  
79 for example the adaptive importance of seed dormancy for summer drought avoidance  
80 (Kronholm, Picó, Alonso-Blanco, Goudet, & Meaux, 2012), the adaptive re-modeling of  
81 trade-offs between life-history traits across the species range (Debieu et al., 2013), the  
82 importance of pre-adaptation to climate for biological invasions (Hamilton, Okada, Korves, &  
83 Schmitt, 2015) or the ecological importance of plasticity to environmental stress (Lasky et al.,  
84 2014).

85 Natural variation in stomatal patterning is known to segregate in *Arabidopsis thaliana*  
86 (Delgado, Alonso-Blanco, Fenoll, & Mena, 2011), but so far technical limitations have  
87 complicated the phenotyping of stomatal variation on larger samples. Here, we developed an  
88 automated confocal microscopy approach that overcomes this limitation and characterized  
89 genetic variation in stomatal patterning in 330 fully-sequenced accessions, across a North-  
90 South transect of the European range. Additionally, we measured  $\delta^{13}\text{C}$ , a measure of water-  
91 use efficiency, for all genotypes. Combined with public genomic and environmental  
92 resources, this dataset allows us to ask i) how much genetic variation of stomata patterns is in  
93 natural *A. thaliana* populations? ii) does variation in stomata patterning influence the carbon-  
94 water trade-off, iii) what is the genetic architecture of stomata variation? iv) is variation in

95 stomata patterning impacted by natural selection and v) what ecological parameters determine  
96 the selective force?

97 We find that genetic variation for stomata size correlates negatively with both stomata density  
98 and water-use efficiency, reflected by  $\delta^{13}\text{C}$ . Using estimates from multi-trait mixed models  
99 (MTMM, (Korte et al., 2012), we show that the correlation between stomata size and  $\delta^{13}\text{C}$  is  
100 determined by a common, yet highly polygenic genetic basis. The correlation between  
101 stomata size and density, instead, did not show a detectable common genetic basis. In  
102 addition, genome-wide association studies (GWAS) revealed two novel QTL that control  $\delta^{13}\text{C}$   
103 independent of stomata size. We conclude that stomatal patterning contributes to some of the  
104 modulation of water-use efficiency. Patterns of variation with environmental variables  
105 suggest, nevertheless, that each of these traits evolves under local selective pressures.

## 106 **Methods**

### 107 **Plant material, plant genotypes and growth conditions**

108 In total, 330 accessions, spanning a wide geographical range were selected from the 1001  
109 collection of fully sequenced genotypes (Suppl. Table 1). Accessions were assigned to 5  
110 groups based on their geographic origin: Spain, Western Europe, Central Europe, South  
111 Sweden and North Sweden (Figure S1). The genome sequences of the 330 genotypes included  
112 in the analysis were downloaded from the 1001 genome database (Alonso-Blanco et al., 2016)  
113 on May 12th, 2017. For population genomic analysis, single Nucleotide Polymorphism (SNP)  
114 data were extracted using *vcftools* (Danecek et al., 2011). SNPs were randomly thinned to one  
115 variant per kilobase, which is the approximate extent of linkage disequilibrium in *A. thaliana*  
116 (Nordborg et al., 2002). Additionally, minimum minor allele frequency was set to 5% and  
117 sites with more than 5% missing data were removed, resulting in 70,410 SNPs among all

118 genotypes. SNP information was loaded into R using the *vcfR* package (Knaus, Grunwald,  
119 Anderson, Winter, & Kamvar, 2017). For genome-wide association studies the full SNP data  
120 set was used and missing SNPs were imputed using BEAGLE version 3.0 (Browning &  
121 Browning, 2009).  
122 Seeds were stratified on wet paper for 6 days at 4°C in the dark. Plants were grown on soil in  
123 5x5cm paper pots in 3 replicates with one plant per pot. Genotypes were randomized within  
124 each of 3 blocks of 12 trays containing 8x4 pots. Plants were grown for 7 weeks in growth  
125 chambers (one for each block) under following conditions: 16h light; 95  $\mu\text{mol s}^{-1} \text{mm}^{-2}$   
126 light intensity; 20 °C day temperature and 18 °C night temperature. Plants were watered twice  
127 a week and trays were shuffled and rotated every two to three days to account for variable  
128 conditions within the chambers.

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130

### 131 High throughput microscopy

132 After 7 weeks, one fully-expanded intact adult leaf (one of the largest leaves that developed  
133 after leaf 4) was selected on each plant for microscopic analysis. From each leaf, two discs  
134 were cut mid-way along the length of the leaf on both sides of the main vein, using a 6mm  
135 hole punch. If the leaf was too small to cut two discs an additional leaf was collected. The  
136 discs were loaded onto an array of 80 spring mounted stamps with the abaxial side up and  
137 fixed on a thin layer of dental adhesive cream (blend-a-dent Super-Haftcreme). The leaf discs  
138 were stained using 25 $\mu\text{l}$  of a 100 $\mu\text{g/ml}$  propidium iodide solution for specific staining of  
139 stomata and cell walls (Fitzgibbon et al., 2013). A Zellkontakt 96-well glass-bottom plate was  
140 then put on top of the stamp array and fixed using four screws. To infiltrate the leaf discs with  
141 the stain, the plate was put under vacuum three times for one minute. Microscopic images

142 were taken using the Opera High Content Screening System from Perkin Elmer. The  
143 following settings were used: excitation wavelength 561nm; laser power 11000 $\mu$ W;  
144 magnification 20x; camera filter 600/40 nm; dichro filter 568 nm; exposure time 200ms;  
145 binning 1. Images were taken in 15 fields (0.15 mm<sup>2</sup>) per well/sample. For each field 11  
146 images were taken along the z-axis with 3 $\mu$ m distance to acquire image stacks. In total, we  
147 acquired 341,000 microscopic images of abaxial leaf epidermises, resulting in 31,000 image  
148 fields for stomata analysis.

149

150

## 151 [Image analysis](#)

152 The first step of the analysis was performed with the software Acapella from Perkin Elmer.  
153 Images were filtered with a sliding parabola filter to reduce background noise. Image stacks  
154 were then collapsed to a single 2D image using maximum projection. The stomata detection  
155 algorithm was implemented in MATLAB using its Image Processing Toolbox (see Suppl.  
156 Document 1 for detailed description). Briefly, images were pre-filtered based on summary  
157 statistics to remove low quality images, which could not be analyzed. Images were optimized  
158 using noise reduction and contrast enhancement functions and converted to binary images that  
159 contained objects (1 pixels) and background (0 pixels), using an intensity threshold. Stomata  
160 were among these objects but not exclusively. Hence, they were filtered to remove any false  
161 positive detections by using multiple morphological filters based on typical stomata  
162 characteristics (e.g. size, shape, etc.).

163

164



## 165 Stomata phenotypes

166 For each image, the number of stomata was computed and divided by 0.15 mm<sup>2</sup> (area of each  
167 field) to calculate stomata density. The area (size) of stomata in the image was calculated as  
168 the number of pixels of stomata multiplied by the area of a single pixel and a mean stomata  
169 size was computed. For each individual plant, the median of each phenotypes over all images  
170 was extracted. Stomata density was also determined by counting stomata manually on a  
171 random set of 14 individuals as well as on a set of 32 independently-grown individuals.  
172 Automatic and manual measurements were strongly correlated (Pearson correlation  
173 coefficient  $r^2=0.88$ ,  $p \ll 0.01$  and  $r^2=0.81$ ,  $p \ll 0.01$ , for the 14 and 32 individuals Figures S 2-  
174 3). The algorithm however was conservative and tended to slightly under-estimate stomata  
175 numbers. This ensured that stomata area was also correctly quantified.

176

177

## 178 Leaf size measurements

179 For leaf size measurements, each hole-punched leaf was fixed on a gridded A4 paper sheet (8  
180 per page) using transparent tape. Possible gaps in the edge of leaves were closed using a pen.  
181 Paper sheets were then digitized using a common flatbed scanner. Analysis of the resulting  
182 images was performed in MATLAB (see Suppl. Document 1 for detailed description of the  
183 algorithm). Images were split into 8 predefined leaf fields and a 4 cm<sup>2</sup> black reference field  
184 was used to determine the true pixel size in mm<sup>2</sup> for each image. Grayscale values were  
185 inverted and the image was converted to binary format using automatic intensity thresholding.  
186 Small objects (clutter) were removed using an area opening function. Leaves were identified  
187 as large objects of white pixels. Holes in the leaf surface (from the microscopy samples) were

188 closed. Leaf area was measured as the number of white pixels multiplied by the pixel size in  
189 mm<sup>2</sup>.

190

191

## 192 Carbon isotope discrimination measurements

193 The rosettes of block 1 were placed in individual paper bags after microscopic imaging was  
194 completed and dried at 70 °C for 3 weeks. Plant material was then ground to fine powder  
195 using a 25mm steel bead and a mixer mill (Retsch, MM 301). Isotope composition was  
196 determined using an ISOTOPE cube elemental analyzer coupled to an Isoprime 100 isotope  
197 ratio mass spectrometer (both from Elementar, Hanau, Germany) according to (Gowik,  
198 Bräutigam, Weber, Weber, & Westhoff, 2011). The carbon isotope ratio is expressed as ‰  
199 against the Vienna Pee Dee Belemnite (VPDB) standard.

200

201

## 202 Heritability estimates

203 Broad sense heritability  $H^2$ , the proportion of the observed phenotypic variance that is genetic,  
204 was estimated as:

$$H^2 = \text{Var}G / (\text{Var}G + \text{Var}E)$$

205 where VarG is the genetic variance and VarE is the environmental variance. Because we  
206 worked with inbred lines, the environmental and genetic variance components can be  
207 estimated as the variance between replicates of a genotype and the variance between  
208 genotypes, respectively, with a linear-mixed-model using block as fixed effect and genotype  
209 as random effect. We ran a linear mixed model using the *lme* function from *nlme* package  
210 (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2015). For  $\delta^{13}\text{C}$ , no replicates were

211 available but a pseudo-heritability estimate was extracted from the GWAS mixed model  
212 including the kinship matrix (Atwell et al., 2010).

213

214

## 215 **Genome-Wide Association Study (GWAS)**

216 Phenotypic measures including 330 genotypes for stomata density and stomata size, and 310  
217 genotypes for  $\delta^{13}\text{C}$  were deposited in the AraPheno database (Seren et al., 2017). For 261  
218 genotypes, all three phenotypes were determined. GWAS was performed for 2.8-3M SNPS  
219 with frequency  $>0.019$  with a mixed model correcting for population structure with a kinship  
220 matrix calculated under the assumption of the infinitesimal model. Each marker was first  
221 analyzed with a fast approximation (Kang et al., 2010) and the 1000 top-most associated  
222 SNPs were reanalyzed with the full model following previously described methods (Atwell et  
223 al., 2010). R scripts (R Development Core Team, 2008) are available at  
224 <https://github.com/arthurkorte/GWAS>.

225 For trait pairs measured on the same plants, a Multi-trait Mixed Model (MTMM) was applied  
226 to distinguish common and trait-specific SNP/phenotype association (Korte et al., 2012) . The  
227 MTMM analysis also provides estimates of genetic and environmental correlation for each  
228 pair of traits. The R scripts are available at <https://github.com/Gregor-Mendel-Institute/mtmm>  
229 The significance threshold was determined as a Bonferroni threshold, e.g. 0.05 divided by the  
230 number of polymorphic SNPs in the dataset.

231

232

## 233 Climatic data

234 Climatic data included average precipitation, temperature, water vapor pressure (humidity),  
235 wind speed and solar radiation estimates with 2.5 min grid resolution (WorldClim2 database  
236 (Fick & Hijmans, 2017) on May 30<sup>th</sup>, 2017) and soil water content (Trabucco & Zomer,  
237 2010). For each variable and accession, we extracted a mean over the putative growing  
238 season, i.e. the months in the year with average temperature greater than 5 °C and average soil  
239 water content over 25% (Suppl. Table 1). We further computed historical drought frequencies  
240 at *A. thaliana* collection sites using 30+ years of the remotely-sensed Vegetative Health Index  
241 (VHI). The VHI is a drought detection method that combines the satellite measured  
242 Vegetative Health and Thermal Condition Indices to identify drought induced vegetative  
243 stress globally at weekly, 4km<sup>2</sup> resolution (Kogan, 1995) . This is a validated method for  
244 detecting drought conditions in agriculture (Kogan, 1995), which may select for alternative  
245 drought tolerance physiologies. Specifically, we used VHI records to calculate the historic  
246 frequency of observing drought conditions (VHI<40) during the spring (quarter surrounding  
247 spring equinox) and summer (quarter surrounding summer solstice). Spring and summer  
248 drought frequencies were transformed into a univariate descriptor of historic drought regimen  
249 as the log transformed spring to summer drought frequency ratio. This variable describes the  
250 relative risk of experiencing drought in spring vs. summer (Suppl. Table 1). Because these 7  
251 variables are correlated, we combined them in 7 orthogonal principal components for 316 *A.*  
252 *thaliana* collection sites (Figures S4-6, loadings described in Suppl. Document 2). Fourteen  
253 genotypes with missing climate data were excluded. Climatic distance between each region  
254 pair was estimated as the F-statistic of a multivariate analysis of variance (MANOVA) with  
255 climatic PCs as response variables and region of origin as the predictor.

256

257

## 258 Population genomic analysis

259 Principal component analysis was done using the *adegenet* package (function *dudi.pca*)  
260 (Jombart et al., 2016), with scaled variants (NA converted to mean) (Figures S7-8). Genome-  
261 wide  $F_{ST}$  estimates were calculated using the *hierfstat* package (function *basic.stats*) (Goudet,  
262 2005). Negative  $F_{ST}$  values were set to zero and the 95th percentile was calculated using the  
263 *quantile* function.

264 The phenotypic differentiation between regions,  $Q_{ST}$ , was estimated as:

$$Q_{st} = VarB / (VarW + VarB)$$

265 where  $VarW$  is the variance within regions and  $VarB$  the variance between regions as  
266 described in Kronholm et al., 2012. Variance components were estimated with the *lme* function  
267 mentioned previously, including block as a fixed effect and genotype within region as a  
268 random effect. We used the genotype effect as an estimate for within region variance and the  
269 region effect as an estimate for between region variance. Because we did not measure  
270 replicates for  $\delta^{13}C$ , we could not estimate the environmental variance component. Thus, we  
271 adapted the model to include only region as a random effect, which was our estimate of  
272 between region variance and used the residual variance as within region variance. This  
273 approach underestimates  $Q_{ST}$  and its use for detecting signatures of local adaptation at the  
274 phenotypic level is conservative.

275 To test whether  $Q_{ST}$  estimates significantly exceed the 95<sup>th</sup> percentile of the  $F_{ST}$  distribution,  
276 we permuted the phenotypic data in a way that heritability remained constant, e.g. by  
277 randomizing genotype labels. For each permutation and phenotype, we calculated the  
278 difference between each  $Q_{ST}$  value and the 95<sup>th</sup> percentile of the  $F_{ST}$  distribution. We used the

279 95th percentile of the maximum  $Q_{ST}$ - $F_{ST}$  distance distribution as a threshold for determining if  
280 phenotypic differentiation significantly exceeds neutral expectations.

281

282

### 283 Statistical analysis

284 Statistical analysis was conducted using R (R Development Core Team, 2008) (see Suppl.

285 Document 2 for R Markdown documentation). All plots were created using the *ggplot2*

286 (Wickham, 2009), *ggthemes* (Arnold et al., 2017), *ggmap* (Kahle & Wickham, 2013),

287 *ggbiplot* (Vu, 2011) and *effects* (Fox et al., 2016) libraries.

288 We used Generalized Linear Models (GLM) to test the effect of block, origin, position in tray

289 and leaf size on each phenotype (stomata density, stomata size and  $\delta^{13}C$ ). Error distribution

290 was a quasipoisson distribution for stomata density and size and a gaussian for  $\delta^{13}C$ . Stomata

291 density was log-transformed to avoid overdispersion. Significance of each predictor was

292 determined via a type II likelihood-ratio test (*Anova* function of the *car* package). Significant

293 differences between regions were determined with Tukey's contrasts using the *glht* function

294 of the *multcomp* package (Hothorn et al., 2017). GLM Models were also used to test the

295 impact of all climatic principal components on phenotypic traits, while accounting for

296 population structure with the first 20 principal components for genetic variation, which

297 explain 28% of total genetic variation (see above). Additionally, for  $\delta^{13}C$  we also tested a

298 simpler model where the climatic parameter was included but not the population structure.

299 From the resulting models, we created effect plots for significant environmental principal

300 components using the *effects* package (Fox et al., 2016).

301

302

## 303 Results

### 304 Significant genetic variation in stomata patterning

305 We analyzed over 31,000 images collected in three replicate plants of 330 *A. thaliana*  
306 genotypes and observed high levels of genetic variation in stomata patterning. Genotypic  
307 means ranged from 87 to 204 stomata/mm<sup>2</sup> for stomata density and from 95.0 μm<sup>2</sup> to 135.1  
308 μm<sup>2</sup> for stomata size (see Suppl. Table 2 for raw phenotypic data). Leaf size was not  
309 significantly correlated with stomata density ( $r=-0.02$ ,  $p=0.7$ ) and stomata size ( $r=-0.08$ ,  
310  $p=0.15$ ), as expected in fully developed leaves. Broad-sense heritability ( $H^2$ ) reached 0.37 and  
311 0.29 for stomata size and density, respectively. Mean stomata density and stomata size were  
312 negatively correlated ( $r=-0.51$ ,  $p<<0.001$ ; Figure 1), a pattern that has been commonly  
313 reported (Hetherington & Woodward, 2003). Due to this strong correlation, we focus  
314 primarily on stomata size in the following report, but results for stomata density can be found  
315 in the supplemental material.

316

317

### 318 Stomata size correlates with water-use efficiency

319 We expected variation in stomatal traits to influence the trade-off between carbon uptake and  
320 transpiration. Thus, we measured isotopic carbon discrimination,  $\delta^{13}\text{C}$ , an estimator that  
321 increases with water-use efficiency (WUE) (Farquhar, Hubick, Condon, & Richards, 1989;  
322 McKay et al., 2008).  $\delta^{13}\text{C}$  ranged from -38.7‰ to -30.8‰ (Suppl. Table 2) and was  
323 significantly correlated with stomata size ( $r=-0.18$ ,  $p=0.004$ ; Figure 2), indicating that  
324 accessions with smaller stomata have higher WUE. In contrast, we found no significant  
325 correlation between stomatal density and  $\delta^{13}\text{C}$  ( $r=-0.007$ ,  $p=0.9$ , Figure S9).

326

327

### 328 Common genetic basis of stomata size and $\delta^{13}\text{C}$

329 To identify the genetic basis of the phenotypic variance we observe, we conducted a genome-  
330 wide association study (GWAS) for each measured phenotype. Based on the genome-wide  
331 nucleotide differences between genotypes (i.e. the kinship matrix), a pseudo-heritability can  
332 be calculated. Pseudo-heritability estimates were 0.59 for stomata density, 0.56 for stomata  
333 size and 0.69 for  $\delta^{13}\text{C}$ , indicating that differences in stomata patterning and carbon physiology  
334 decreased with increasing relatedness. Despite considerable levels of heritability, we did not  
335 detect any variant associating with stomata density at a significance above the Bonferroni-  
336 corrected p-value of 0.05 ( $\log_{10}(p)=7.78$ ). For stomata size, we detected one QTL with two  
337 SNPs significantly associating at positions 8567936 and 8568437 (Figure S10). These SNPs  
338 have an allele frequency of 1.5% (5 counts) and 2.1% (7 counts), respectively and map to  
339 gene *AT4G14990.1*, which encodes for a protein annotated with a function in cell  
340 differentiation. The former SNP is a synonymous coding mutation while the latter is located  
341 in an intron. This suggests that variation in stomata size and density is primarily controlled by  
342 multiple loci of small effect, with larger effects being contributed by very rare alleles.

343

344 For  $\delta^{13}\text{C}$ , one genomic region on chromosome 2 position 15094310 exceeded the Bonferroni  
345 significance threshold ( $\log_{10}(p)=7.97$ , Figure S11). Allele frequency at this SNP was 9.7% (30  
346 counts) and all accessions carrying this allele, except four, were from South Sweden (3 North  
347 Sweden, 1 Central Europe). Southern Swedish lines carrying the allele showed significantly  
348 increased  $\delta^{13}\text{C}$  compared to the remaining Southern Swedish lines ( $W = 1868$ , p-value =  
349 6.569e-05, Figure S12). A candidate causal mutation is a non-synonymous SNP at position



350 15109013 in gene *AT2G35970.1*, which codes for a protein belonging to the Late  
351 Embryogenesis Abundant (LEA) Hydroxyproline-Rich Glycoprotein family. This SNP also  
352 shows elevated association with the phenotype, however its significance lied below the  
353 Bonferroni threshold ( $\log(p)=7$ ). Since this SNP is not in linkage disequilibrium with the  
354 highest associating SNP in the region (Figure S13), it is possible that another independent  
355 SNP in this region is causing the association.

356

357 We used multi-trait mixed-model (MTMM) analysis to disentangle genetic and environmental  
358 determinants of the phenotypic correlations. We found that the significant correlation between  
359 stomata density and stomata size ( $r = -0.5$ ) had no genetic basis, but had a significant ( $r=-0.9$ ,  
360  $p<0.05$ ) residual correlation. This suggests that the correlation was not determined by  
361 common loci controlling the two traits, but by other, perhaps physical, constraints, or by  
362 epistatic alleles at distinct loci. By contrast, the correlation between stomata size and  $\delta^{13}\text{C}$  ( $r=$   
363  $-0.18$ ) had a significant genetic basis (Kinship-based correlation,  $r=-0.58$ ,  $p<0.05$ ).

364

365 In order to further investigate the genetic basis for the correlation between stomata size and  
366  $\delta^{13}\text{C}$ , we performed MTMM GWAS, which contrasts three models for each SNP: a null  
367 model that includes only global genetic relatedness (kinship), a model including SNP effects  
368 common to both traits and a model including both common and trait-specific marker effects  
369 (Korte et al., 2012). Contrasting these models reveals SNPs that magnify or decrease the  
370 correlation between traits. We did not observe variants increasing genetic correlation between  
371  $\delta^{13}\text{C}$  and stomata size (Figure S14), suggesting that it is controlled by many loci of small  
372 effect. However, in the full model, we observed a marginally significant association on  
373 chromosome 4, which de-correlated the two traits. GWAS of  $\delta^{13}\text{C}$  restricted to the 261

374 individuals used for the MTMM analysis confirmed the QTL on chromosome 4. In this set of  
375 genotypes, 2 SNPS, at position 7083610, and position 7083612, exceeded the Bonferroni-  
376 corrected significance threshold ( $\alpha=0.05$ ) (both  $p=4.8e-09$ , Figure S15). Allele frequency is  
377 14% (37 counts) at these two loci and explains 11% of the observed phenotypic variation. The  
378 association is probably due to complex haplotype differences because it coincides with a  
379 polymorphic deletion and contains several imputed SNPs. As many as 35 of the 37 accessions  
380 carrying the minor allele originated from South Sweden and showed a significantly higher  
381 water use efficiency compared to other Southern Swedish accessions (mean difference=1.34;  
382  $W = 1707$ ,  $p\text{-value} = 1.15e-06$ ; Figure S16). The  $p$ -values of associations with  $\delta^{13}\text{C}$  for the  
383 two datasets (310 and 261 accessions) are highly correlated ( $r=0.87$ ,  $p\ll 0.0001$ , Figure S17).  
384 In summary, we detected two genetic variants that significantly associate with  $\delta^{13}\text{C}$ ,  
385 independent of stomata size, despite the common genetic basis of the two traits.

386

387

### 388 Stomata size and stomata density correlate with geographical patterns of climatic 389 variation

390 We used principal component analysis to describe multivariate variation in climatic  
391 conditions reported for the locations of origins of the genotypes. We tested the correlation of  
392 each measured phenotype with climatic principal components (PC) using a generalized linear  
393 model which accounted for genetic population structure (see methods). We found a  
394 significant, negative relationship between genetic variation in stomatal size and climatic PC2  
395 (Likelihood ratio test Chi-Square (LRT  $X^2$ ) =9.2784, degrees of freedom (df)=1,  $p=0.005$ ) and  
396 PC5 (LRT  $X^2$ = 5.7335, df=1,  $p=0.02$  Figure 3). Climatic PC 2 explained 23.8% of climatic  
397 variation and had the strongest loadings (both negative) from temperature and water vapor

398 pressure (humidity). Climatic PC 5 explained 9% of the climatic variation and mostly  
399 increased with increasing spring-summer drought probability ratio and increasing solar  
400 radiation. We also found significant climatic predictors for the distribution of genetic  
401 variation in stomata density (PC 2: LRT  $X^2= 8.6612$ ,  $df=1$   $p=0.003$ ; PC 5: LRT  $X^2= 7.3773$ ,  
402  $df=1$ ,  $p=0.007$ ; PC 7: LRT  $X^2= 6.6033$ ,  $df=1$ ,  $p=0.01$ ; Figure S18).  $\delta^{13}C$  did not correlate with  
403 any of the climatic PCs. However, removing population structure covariates from the model  
404 revealed significant correlations of  $\delta^{13}C$  with climatic PC2 (+, LRT  $X^2= 7.3564$ ,  $df=1$ ,  
405  $p=0.006$ ), PC3 (-, LRT  $X^2= 3.8889$ ,  $df=1$ ,  $p=0.048$ ) and PC4 (+, LRT  $X^2= 6.6885$ ,  $df=1$ ,  $p=$   
406  $0.009$ ) (Figure S19). PC3 explained 13.7% of climatic variation and principally increased  
407 with rainfall and decreased with spring-summer drought probability ratio. PC4 explained  
408 11.4% of the total variation and mostly increased with wind speed. Therefore, the covariation  
409 of  $\delta^{13}C$  with climatic parameters describing variation in water availability and evaporation in  
410 *A. thaliana* is strong but confounded with the demographic history of the species.

411

412

### 413 Patterns of regional differentiation depart from neutral expectations

414 Genotypes were divided into five groups (regions) according to their geographic origin  
415 (Figure S1). We detected significant phenotypic differentiation among these regions for  
416 stomata size (LRT  $X^2=52.852$ ,  $df=4$ ,  $p=9.151e-11$ , Figure 4). Stomata size was highest in  
417 accessions from Central Europe (mean=114  $\mu m^2$ ) and significantly lower in accessions from  
418 North Sweden (mean=110  $\mu m^2$ , General Linear Hypothesis Test (GLHT)  $z=-2.842$ ,  $p =$   
419  $0.0333$ ) and South Sweden (mean=109  $\mu m^2$ , GLHT  $z=-5.781$ ,  $p<0.001$ ). Spanish accessions  
420 also had significantly larger stomata (mean=112  $\mu m^2$ ) than South Swedish accessions (GLHT

421  $z=6.044$ ,  $p<0.001$ ). Variation for stomata density, which is negatively correlated with stomata  
422 size, showed a similar but inverted pattern (Figure S20).

423

424 Furthermore, we found significant regional differentiation in  $\delta^{13}\text{C}$  measurements (LR  $X^2$   
425  $=58.029$ ,  $df=4$   $p=7.525e-12$ , Figure 4). Highest  $\delta^{13}\text{C}$  levels (highest WUE) were found in  
426 accessions from North Sweden (mean=-34.8) and South Sweden (mean=-35.2), which were  
427 significantly higher than in accessions from Spain (mean=-35.7; GLHT South Sweden  $z= -$   
428  $3.306$ ,  $p=0.008$ ; GLHT North Sweden  $z=-3.77$ ,  $p=0.001$ ) and Western Europe (mean=-36.17;  
429 GLHT South Sweden  $z= -3.108$ ,  $p=0.015$ ; GLHT North Sweden  $z=-3.77$ ,  $p=0.001$ ). Lowest  
430  $\delta^{13}\text{C}$  levels were found in lines from Central Europe (mean=-36.6), which were significantly  
431 lower than in lines from North Sweden (GLHT  $z=6.223$ ,  $p<0.001$ ), South Sweden (GLHT  
432  $z=6.267$ ,  $p<0.001$ ) and Spain (GLHT  $z=4.025$ ,  $p<0.001$ ). These differences are visualized in  
433 Figure 4.

434

435

436 The observed regional differences might result either from the demographic history of the  
437 regions or from the action of local selective forces. To tease these possibilities apart, the  
438 phenotypic differentiation ( $Q_{ST}$ ) can be compared to nucleotide differentiation at the  
439 nucleotide level (Kronholm et al., 2012; Leinonen, McCairns, O'hara, & Merilä, 2013). We  
440 examined each pair of regions separately, since they are not equidistant from each other, and  
441 calculated  $F_{ST}$  distributions for over 70,000 independent SNP markers (spaced at least 1kb  
442 apart, see methods) from the 1001-genome project (Alonso-Blanco et al., 2016). For each  
443 trait,  $Q_{ST}$  exceeded the 95<sup>th</sup> percentile of the  $F_{ST}$  distribution in at least two pairs of regions  
444 (Table 1 A-C). We used permutations to calculate a significance threshold for the  $Q_{ST}/F_{ST}$

445 difference (see methods). Significant regional differentiation was pervasive in our sample,  
446 with Central Europe and South Sweden being significantly differentiated for all four  
447 phenotypes. This analysis suggests that natural selection has contributed to shape the  
448 phenotypic differentiation between regions.

449

450

451 Local differences in climate may have imposed regional divergence in stomatal patterning.  
452 Thus, we estimated climatic distances between regions using estimates of regional effects  
453 extracted from a multivariate analysis of variance. We did not observe significant correlations  
454 between phenotypic divergence as measured by  $Q_{ST}$  and the climatic distance of the  
455 respective regions (Mantel test  $p > 0.05$  for each of the three traits).

456

457

## 458 Discussion

### 459 Genetic variation for stomata patterning segregates in *A. thaliana*

460 We used high-throughput confocal imaging to characterize stomata patterning in over 31,000  
461 images from 870 samples collected from 330 genotypes. Using automated image acquisition  
462 and analysis, we could characterize stomata density and stomata size, with an accuracy  
463 confirmed by the high correlation with manual estimates. Pavement cells could not be  
464 accurately counted, so that stomata indices, which describe the rate of epidermal cell  
465 differentiation (Salisbury, 1928), were not quantified. As a result, the genetic diversity of cell  
466 differentiation processes was not evaluated. Nevertheless, our approach provides a complete  
467 view over the amount of stomata diversity displayed on the leaf surface. This morphological

468 variance is indeed the one that should ultimately have an impact on the stomatal conductance  
469 required for photosynthesis and growth. Broad-sense heritability and pseudo-heritability  
470 estimates for stomata density, which are 29% and 58%, respectively, are slightly lower than in  
471 a previous report of manually counted stomata diversity across a smaller sample chosen to  
472 maximize genetic diversity (Delgado et al., 2011). Despite this relatively low heritability,  
473 stomata size and stomata density showed a strong negative correlation. This is consistent with  
474 earlier reports of studies manipulating regulators of stomata development (Doheny-Adams,  
475 Hunt, Franks, Beerling, & Gray, 2012; Franks et al., 2015), but also with studies analyzing  
476 stomatal trait variation in a wide range of species (Franks & Beerling, 2009; Hetherington  
477 & Woodward, 2003).

478

479 The extensive genomic resources available in *A. thaliana* (Alonso-Blanco et al., 2016)  
480 enabled us to interrogate the genetic basis of trait variation and co-variation, with the help of  
481 genome-wide association studies (GWAS) (Atwell et al., 2010). We did not detect any  
482 genomic region that associated with stomata density at a p-value beyond the Bonferroni  
483 significance threshold and for stomata size there was only one significant association with a  
484 very low frequency allele on chromosome 4. Given the heritability of these two traits, this  
485 shows that many alleles of low frequency and/or small effect contribute to the variation we  
486 observe. Indeed, GWAS studies can detect small effect loci only if they segregate at high  
487 frequency (Korte & Farlow, 2013; Wood et al., 2014). Alternatively, multiple independent  
488 alleles (allelic series) segregating at causal loci may also play a role.

489

490 Using multi-trait GWAS (Korte et al., 2012), we further investigated the impact of genetic  
491 variation on the negative co-variation between stomata size and density. This analysis

492 revealed that genetic similarity does not influence the pattern of co-variation. It implies that  
493 either multiple alleles act epistatically on the covariation, or that physical or environmental  
494 factors explain the correlation.

495

496

497 [Polygenic variation in stomata patterning can contribute to optimize physiological](#)  
498 [performance](#)

499 Both stomata development and reactions to drought stress stand under intense scrutiny in *A.*  
500 *thaliana* (Bergmann & Sack, 2007; Krasensky & Jonak, 2012; Pillitteri & Torii, 2012;  
501 Verslues, Govinal Badiger, Ravi, & M. Nagaraj, 2013). Mutants in stomata density or size  
502 have recently been shown to have a clear impact carbon physiology (Franks et al., 2015;  
503 Hepworth, Doheny-Adams, Hunt, Cameron, & Gray, 2015; Hughes et al., 2017; S. S.  
504 Lawson, Pijut, & Michler, 2014; Masle, Gilmore, & Farquhar, 2005; Yoo et al., 2010; Yu et  
505 al., 2008). Yet, the relevance of natural variation in stomatal patterning for facing up with  
506 local limitation in water availability had not been documented in this species so far. We  
507 provide here concomitant measures of morphological and physiological variation to examine  
508 the impact of variation in stomatal patterning on natural variation in carbon uptake. In a small  
509 number of populations in the close relative *A. lyrata ssp. lyrata*, smaller stomata size indeed  
510 coincided with increased WUE as a plastic response to water limitation (Paccard et al., 2014).  
511 By including genome-wide patterns of nucleotide diversity, our analysis presents two major  
512 findings: i) the increase in stomata size associates with a decrease in water-use efficiency in  
513 *A. thaliana* and ii) this pattern of co-variation has a genetic basis. This shows that, in *A.*  
514 *thaliana*, variation in stomata size has the potential to be involved in the optimization of  
515 physiological processes controlling the trade-off between growth and water loss.

516

517 While variation for stomata size and density displayed a largely polygenic basis, without large  
518 effect alleles, we detected two regions in the genome that associated significantly with carbon  
519 isotope discrimination. Three previous QTL mapping analyses, including one between  
520 locally adapted lines from Sweden and Italy, identified 16 distinct QTLs controlling  $\delta^{13}\text{C}$   
521 (Juenger et al., 2005; McKay et al., 2008). (Mojica et al., 2016). One of these is caused by a  
522 rare allele in the root-expressed gene *MITOGEN ACTIVATED PROTEIN KINASE 12* (*MPK-*  
523 *12*), (Juenger et al., 2005)(Campitelli, Des Marais, & Juenger, 2016). The two QTL we report  
524 here on chromosomes 2 and 4 add two novel loci, raising to 18 the number of genomic  
525 regions known to impact  $\delta^{13}\text{C}$  in *A. thaliana*. The novel loci we report, however, are locally  
526 frequent. Individuals carrying the minor alleles of both loci are almost exclusively from South  
527 Sweden and display significantly higher  $\delta^{13}\text{C}$  than other Southern Swedish accessions.

528 Interestingly, the accessions with the minor allele associating with high  $\delta^{13}\text{C}$  in both QTL did  
529 not show decreased stomata size compared to other accessions. Multi-trait GWAS confirmed  
530 that these QTL are associated with  $\delta^{13}\text{C}$  variants that are independent of genetic variation for  
531 stomata patterning. We therefore can conclude that, while variation in stomata patterning can  
532 contribute to the optimization of carbon discrimination, the reverse does not hold. Carbon  
533 isotope discrimination, and hence WUE, can be optimized without modifying stomata  
534 patterning. A large array of molecular and physiological reactions is indeed known to  
535 contribute to tolerance to drought stress (Krasensky & Jonak, 2012; Verslues et al., 2013).

536 The close vicinity of the chromosome 2 QTL to a non-synonymous mutation in a gene  
537 encoding an LEA protein, known to act as a chaperone when cells dehydrate, suggests one  
538 possible mechanism by which water-use efficiency might be optimized independently of  
539 stomata size and density (Candat et al., 2014; Eriksson, Kutzer, Procek, Gröbner, & Harryson,



540 2011; Reyes et al., 2005). Variation in rates of proline accumulation in the presence of  
541 drought stress or in nutrient acquisition in the root are also among the physiological  
542 mechanism that appear to have contributed to improve drought stress tolerance in this species  
543 (Campitelli et al., 2016; Kesari et al., 2012).

544  
545

546 [Adaptive evolution of stomata patterning is suggested by the geographic distribution](#)  
547 [of genetic variation](#)

548 Phenotypic variation for stomata patterning and carbon uptake is not uniformly distributed  
549 throughout the species range. All three phenotypes we report in this study were significantly  
550 differentiated between the five broad regions defined in our sample of 330 genotypes. We  
551 performed a comparison of phenotypic and nucleotide levels of divergence in order to  
552 evaluate the putative role of past selective events in shaping the distribution of diversity we  
553 report (Leinonen et al., 2013; Whitlock & Guillaume, 2009). Because these regions are not  
554 equally distant,  $F_{ST}/Q_{ST}$  comparisons averaged over all populations may mask local patterns of  
555 adaptation (Leinonen et al., 2013). We therefore measured  $Q_{ST}$  between pairs of regions and  
556 compared them to the distribution of pairwise  $F_{ST}$ , using permutations to establish the  
557 significance of outlier  $Q_{ST}$ . This analysis showed that differentiation between regions was  
558 stronger than expected from genome-wide patterns of diversity. Moreover, stomata density  
559 and stomata size correlated with climatic principal components, which are most strongly  
560 driven by temperature, humidity, solar radiation, and historic drought regimen. The strongest  
561  $Q_{ST}-F_{ST}$  differences are found across regional pairs including Central Europe, in particular  
562 between Central Europe and South Sweden. This somewhat counterintuitive result is  
563 supported by an independent study showing that Swedish genotypes maintain photosynthetic

564 activity for a longer time in the absence of water supply (Exposito-Alonso et al., 2017).  
565 Locally adapted genotypes from Southern Sweden have also been shown to display higher  
566 water-use efficiency than Italian genotypes (Mojica et al., 2016). This regional difference in  
567 *A. thaliana* further coincides with the satellite measurements of historic drought regimen,  
568 which show that South Sweden is a region where drought frequency is high in the spring  
569 compared to summer. Geographic differences in the seasonal window in which drought is  
570 more frequent may select for alternative strategies for facing this threat. In Southern European  
571 regions, for example, *A. thaliana* appeared to rely on escape strategies provided by increased  
572 seed dormancy (Kronholm et al., 2012). In Northern Europe, increased negative co-variation  
573 between flowering time and seed dormancy suggested that the narrow growth season imposes  
574 a strong selection on life-history traits (Debieu et al., 2013). Taken together, this suggest that  
575 decreased stomata size and, consequently, increased  $\delta^{13}\text{C}$  may have contributed to adaptation  
576 to water limitations in spring in a region where the narrow growth season leaves no room for  
577 escape strategies. Indeed, both stomata size and  $\delta^{13}\text{C}$  associate with historic drought regimen.  
578 For  $\delta^{13}\text{C}$ , however, this is only the case when genetic population structure is not included as a  
579 covariate. This indicates that local adaptation for water-use efficiency might have also  
580 contributed to shape the current population structure. In addition, regional contrasts will mask  
581 any pattern of local adaptation occurring at a fine-grained scale within regions. It is therefore  
582 possible that we underestimate the magnitude of adaptive differentiation between regions,  
583 which could further explain why  $Q_{\text{ST}} / F_{\text{ST}}$  differences did not co-vary with environmental  
584 divergence in our dataset.  
585  
586

## 587 Conclusion

588 This work provides a comprehensive description of the variation in stomata size and density  
589 that segregates throughout the range of the annual species *A. thaliana*. Although stomata  
590 differentiation is a prominent model for the study of the mechanisms controlling cellular  
591 differentiation, not much is known about the importance of stomata size and density for the  
592 optimization of gas exchanges. Co-variation with measures of carbon physiology now suggest  
593 that stomata size is one of the factors contributing to the local optimization of trade-offs  
594 between carbon fixation and limitation of water loss.

595 This work only examined how stomata patterning impacts physiological performance under  
596 conditions where water is not limiting. Future work will have to investigate whether this  
597 source of genetic variation also contributes to environmental plasticity, both in stomatal  
598 development and in carbon isotope discrimination. The closing of stomata is indeed an  
599 important reaction to drought stress, and stomata size is known to influence the rate of  
600 stomatal closing (Drake et al., 2013; T. Lawson & Blatt, 2014). In addition, several reports  
601 indicate that plants can plastically adjust stomatal development in water-limiting conditions  
602 (Fraser, Greenall, Carlyle, Turkington, & Friedman, 2009; Paccard et al., 2014; Xu & Zhou,  
603 2008).

604

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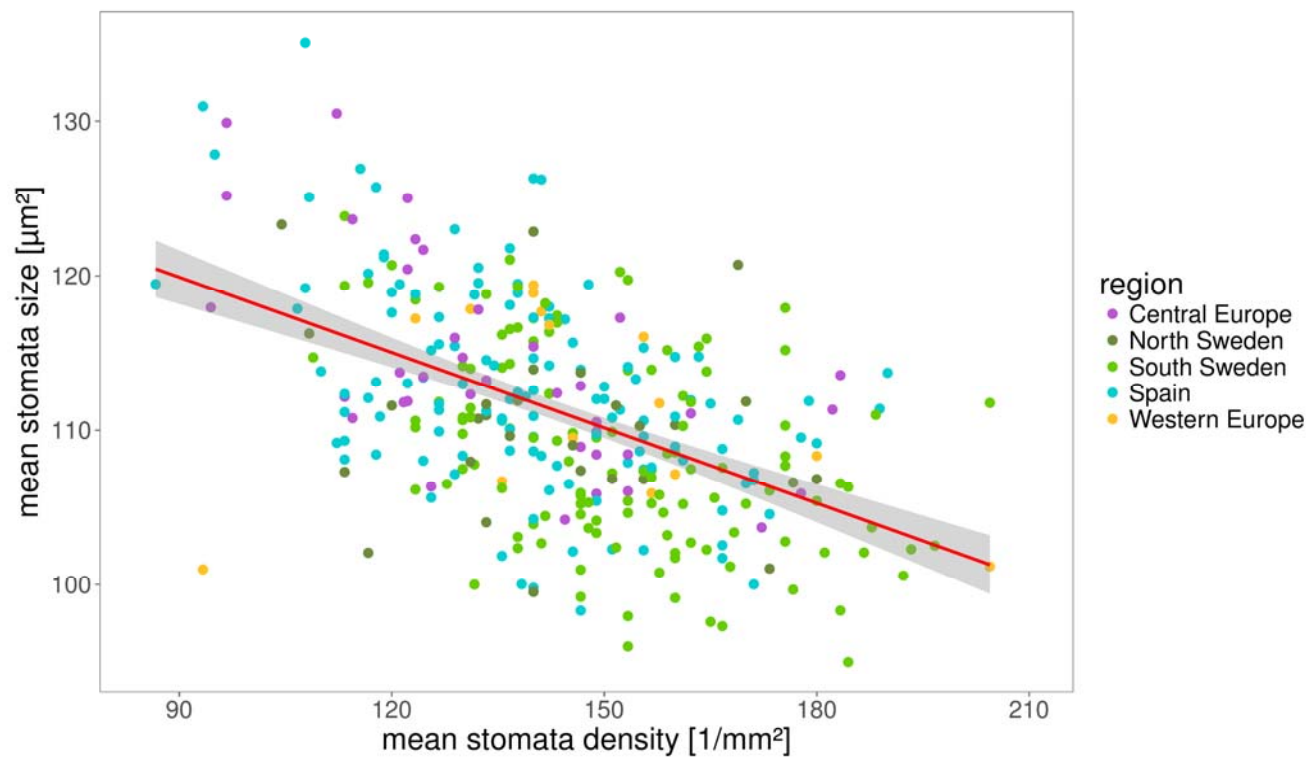
## Data accessibility

Raw image data and image analysis scripts are available upon request and will be stored in a Dryad repository upon acceptance. All phenotypic data is provided in the supplemental material and will be uploaded to the AraPheno database (<https://arapheno.1001genomes.org>, (Seren et al., 2017) and stored in a Dryad repository upon acceptance. Additionally, we provide an R Markdown file, which contains all figures (except GWAS and MTMM) and the corresponding R code used to create the figures and statistics in the supplemental material. GWAS scripts are available at <https://github.com/arthurkorte/GWAS>. MTMM scripts are available at <https://github.com/Gregor-Mendel-Institute/mtmm>. Genomic data used is publicly available in the 1001 genomes database (Alonso-Blanco et al., 2016)

## Author contributions

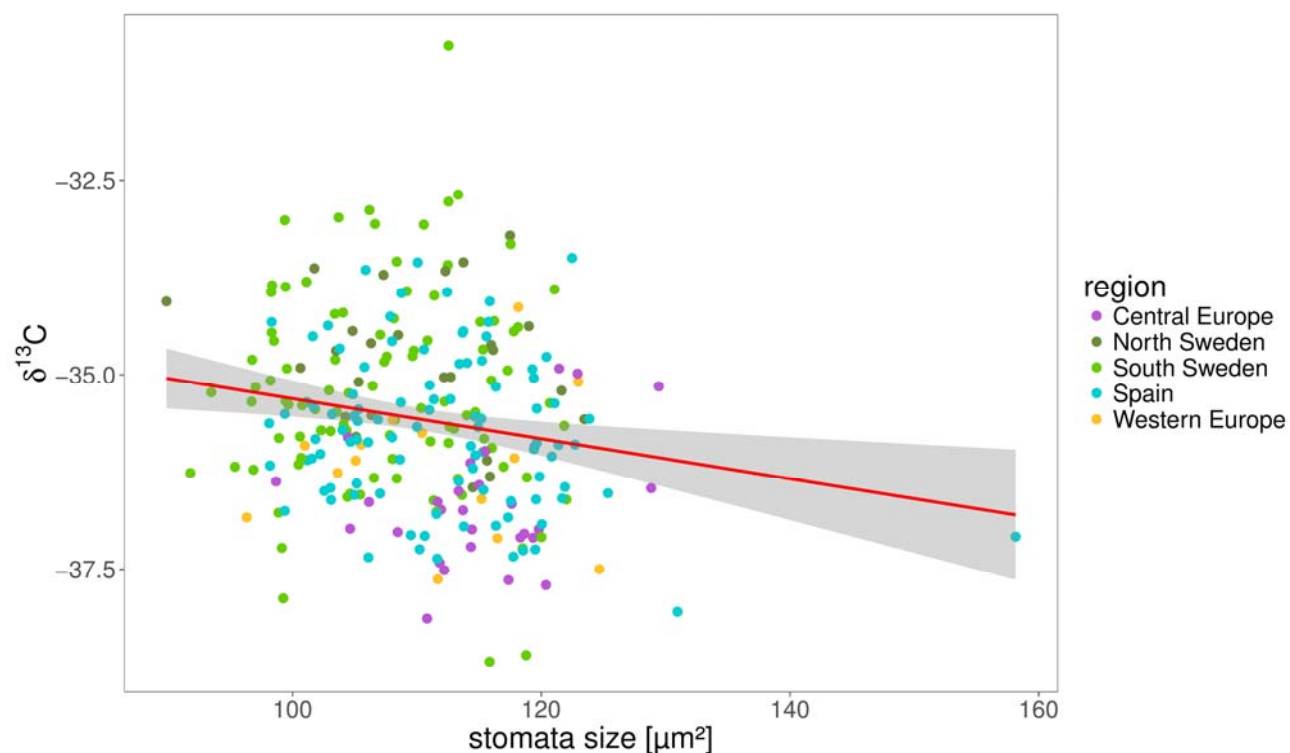
JdM, AK, and HD conceived the study. HD conducted the experiment and produced phenotypic data for stomata traits. TM and AW were responsible for  $\delta^{13}\text{C}$  measurements. GM provided data on historic drought regimen. JdM, AK and HD were responsible for the statistical analyses of the data. JdM and HD wrote the manuscript with significant contributions from AK, TM, AW and GM.

## Figures & Tables



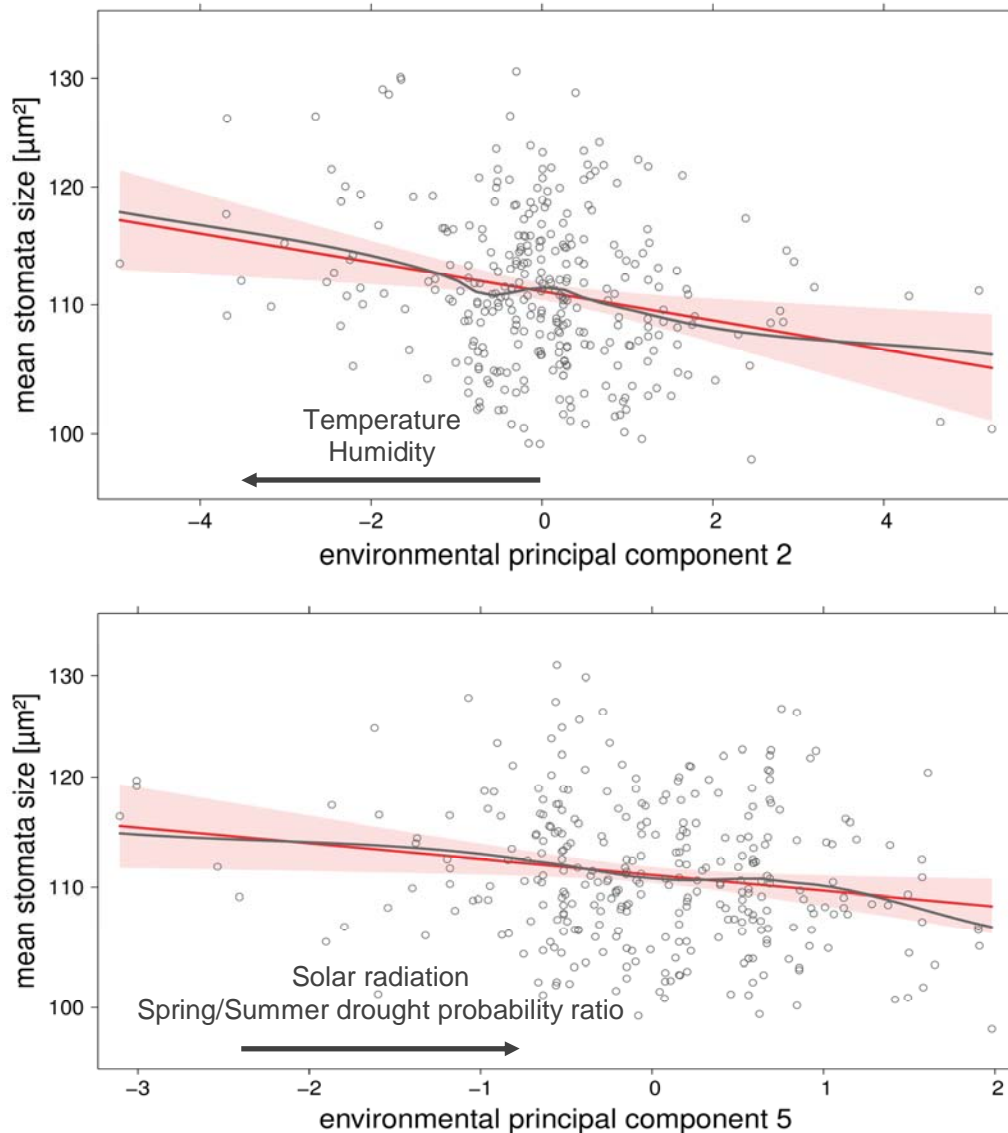
**Figure 1: Natural variation in stomata patterning**

Stomata density and size were measured for 330 natural genotypes of *A. thaliana*. The plot shows genotypic means of stomata density and stomata size. Dots are colored based on the geographical origin of each accession. The red line shows a linear fit and gray shadows indicate the error of the fit. Pearson's product-moment correlation  $r=-0.5$ ,  $p<0.001$ .



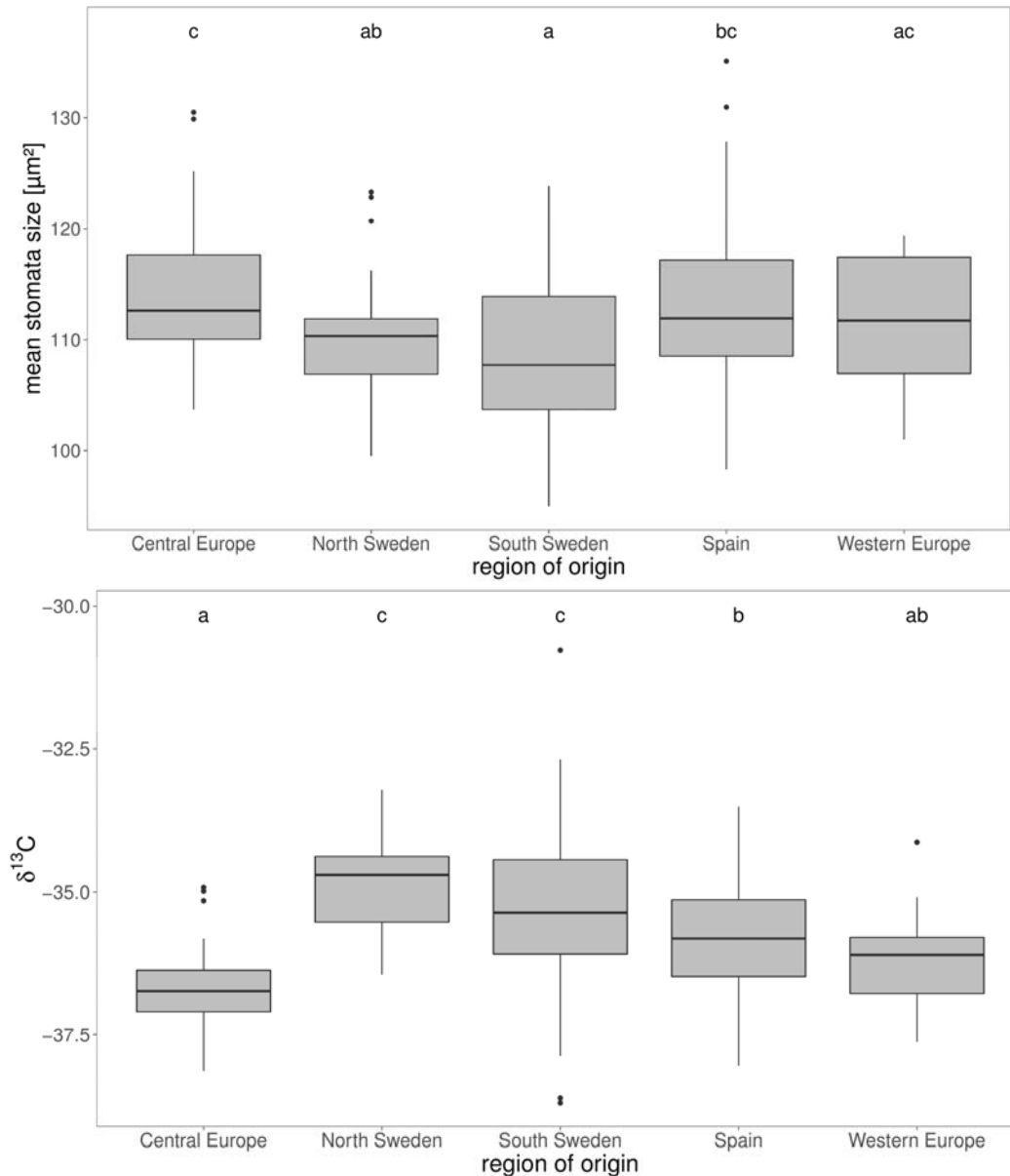
**Figure 2: Stomata size correlates with water-use efficiency**

$\delta^{13}\text{C}$  was measured for all plants in block 1. Plots show correlation of stomata size (block 1 only) with  $\delta^{13}\text{C}$ .  $\delta^{13}\text{C}$  is expressed as ‰ against the Vienna Pee Dee Belemnite (VPDB) standard. The red line shows a linear fit and gray shadows indicate the error of the fit. Pearson's product-moment correlation:  $r=-0.18$ ,  $p=0.004$ ). Correlation of  $\delta^{13}\text{C}$  and stomata size is not only driven by the Spanish outlier (correlation without outlier:  $r=-0.16$ ,  $p=0.009$ ).



**Figure 3: Stomata patterns correlate with geographical patterns of climatic variation**

Correlation between stomata patterns and all seven climatic principal components (PCs) was tested for each phenotype using a Generalized Linear Model (GLM) including genetic population structure as described by the 20 first genetic PCs. Plots are effect plots based on the GLM (see methods), showing the correlation between stomata size two climatic PCs. Black arrows indicate correlation with the climatic variables showing the strongest loadings for the respective principal component. Plots show the linear fit (red solid line) and the smoothed fit of partial residuals (gray) of the specific predictor. Gray dots are partial residuals. The red shade shows the error of the linear fit. Both principal components shown here are significant predictors of the respective response variable ( $p < 0.05$ ). Results for stomata density are similar but inversed due to negative correlation of the traits (Figure S18).



**Figure 4: Significant regional differentiation of stomata size and  $\delta^{13}\text{C}$**

*A. thaliana* accessions were grouped based on their geographical origin. Boxplots show regional differentiation of stomata size (top) and  $\delta^{13}\text{C}$  (bottom). Significance of differentiation was tested using Generalized Linear Models followed by a post-hoc test. Statistical significance is indicated by letters on top: Groups that do not share a common letter are significantly different. Significance levels: top) a-c, a-bc:  $p < 0.001$ ; ab-c:  $p < 0.05$ ; bottom) a-c, a-b:  $p < 0.001$ , b-c:  $p < 0.01$ , ab-c:  $p < 0.05$ .

### A) Stomata size

$Q_{ST} \setminus Q_{ST-F_{ST}}$	Central Europe	North Sweden	South Sweden	Spain	West. Europe
Central Europe		-0.31	<b>0.24</b>	-0.17	-0.16
North Sweden	0.17		-0.38	-0.39	-0.53

South Sweden	0.35	0.03		0.06	-0.02
Spain	<0.01	0.07	0.25		-0.18
West. Europe	<0.01	<0.01	0.16	<0.01	

### B) Stomata density

$Q_{ST} \setminus Q_{ST}-F_{ST}$	Central Europe	North Sweden	South Sweden	Spain	West. Europe
Central Europe		-0.44	<b>0.20</b>	-0.18	<b>0.08</b>
North Sweden	0.04		-0.29	-0.46	-0.47
South Sweden	0.31	0.11		<b>0.08</b>	-0.19
Spain	<0.01	<0.01	0.26		<b>0.07</b>
West. Europe	0.24	0.06	<0.01	0.25	

### C) $\delta^{13}C$

$Q_{ST} \setminus Q_{ST}-F_{ST}$	Central Europe	North Sweden	South Sweden	Spain	West. Europe
Central Europe		<b>0.21</b>	<b>0.26</b>	<b>0.16</b>	-0.11
North Sweden	0.7		-0.36	-0.17	-0.04
South Sweden	0.38	0.04		-0.11	-0.01
Spain	0.34	0.28	0.08		-0.08
West. Europe	0.05	0.49	0.17	0.1	

**Table 1 A-C: Patterns of regional differentiation depart from neutral expectations**

Pairwise  $Q_{ST}$  estimates were derived from linear mixed models for all regions. Genome-wide, pairwise  $F_{ST}$  distribution was calculated based on 70,000 SNPs for all regions. In the top half of each table, the difference  $Q_{ST}-F_{ST}$  for each pair of regions is shown. In the bottom half of each table the  $Q_{ST}$  estimate for each pair of regions is shown. Each table represents one phenotype as indicated by table headlines. Significant  $Q_{ST}-F_{ST}$  differences are written in bold. The significance threshold is based on the 95<sup>th</sup> percentile of a distribution of maximum  $Q_{ST}-F_{ST}$  values from 1000 random permutations of phenotypic data.