

GWAS identifies candidate genes controlling adventitious rooting in *Populus trichocarpa*

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1 **Abstract**

2 Adventitious rooting is critical to the propagation, breeding, and genetic engineering or
3 editing of trees. The capacity for plants to undergo these processes is highly heritable; however,
4 the basis of its genetic variation is largely uncharacterized. To identify genetic regulators of these
5 processes, we performed a genome-wide association study (GWAS) using 1,148 genotypes of
6 *Populus trichocarpa*. GWAS are often limited by the abilities of researchers to collect precise
7 phenotype data on a high-throughput scale; to help overcome this limitation, we developed a
8 computer vision system to measure an array of traits related to adventitious root development in
9 poplar, including temporal measures of lateral and basal root length and area. GWAS was
10 performed using multiple methods and significance thresholds to handle non-normal phenotype
11 statistics, and to gain statistical power. These analyses yielded a total of 277 unique associations,
12 suggesting that genes that control rooting include regulators of hormone signaling, cell division
13 and structure, and reactive oxygen species signaling. Genes related to other processes with
14 known roles in root development, and numerous genes with uncharacterized functions and/or
15 cryptic roles, were also identified. These candidates provide targets for functional analysis,
16 including physiological and epistatic analyses, to better characterize the complex polygenic
17 regulation of adventitious rooting.

18 **Introduction**

19 The species within the genus *Populus spp.* (poplar) are among the most rapidly-growing
20 trees of the northern hemisphere (Dickmann & Stuart, 1983) and have outsized roles in natural
21 ecosystems as keystone species (Brunner *et al.*, 2004; Kouki *et al.*, 2004; Bailey & Whitham,
22 2006; Kivinen *et al.*, 2020). They are also of major economic importance for agroforestry, and as
23 sources of wood, fiber, and biofuel (Sun *et al.*, 2021; Fuertes *et al.*, 2021). In either context, the
24 growth and asexual propagation of poplar relies on the rapid establishment, proliferation and
25 maintenance of a robust root system for nutrient and water absorption. Elite hybrid clones of
26 poplar are propagated in stool beds through a process that relies on the ability of cuttings to
27 undergo adventitious rooting (Stanton *et al.*, 2019). In addition, asexual reproduction of poplar in
28 nature commonly occurs via the process of “root sprouting” from existing roots or the root-shoot
29 junction zone (Wiehle *et al.*, 2009). Moreover, biotic and abiotic stresses such as waterlogging
30 and pest damage often interfere with above-ground tree health by damaging root systems
31 (Brandt *et al.*, 2003; Štícha *et al.*, 2016), a stress that is certain to be exacerbated by climate

32 change (Overpeck & Udall, 2020; Gullino *et al.*, 2021). A deeper understanding of the genes that
33 control rooting may provide new insights into means for improved propagation of recalcitrant
34 genotypes and species, options for improvement of regeneration during genetic
35 engineering/editing, and suggest new strategies for mitigating stress in managed and wild
36 populations.

37 Adventitious rooting in poplar is a highly complex trait that is regulated by many factors,
38 including plant age, genotype, and physiology; the many forms of plant stress; and
39 environmental cues such as temperature, photoperiod, and nutrients. These act through
40 phytohormone signaling cascades that lead to differentiation and development of root tissue.
41 Overexpression and RNAi-mediated suppression of over two dozen genes involved in
42 phytohormone synthesis and response have been reported to lead to increased or decreased
43 adventitious root formation and/or root growth (reviewed by Bannoud & Bellini, 2021). These
44 root-related traits have been shown to be genotype-dependent, with phenotypic variation across
45 *Populus spp.* depending in large part on variable sequence and expression of phytohormone-
46 related genes, especially those involved in auxin pathways or crosstalk between auxin and other
47 phytohormones (Ribeiro *et al.*, 2016; Sun *et al.*, 2019). Genome-wide association studies
48 (GWAS) provide opportunity for insight into how variation in root-related traits across
49 genotypes results from variation in these phytohormone regulators and other genes. To date,
50 GWAS of adventitious rooting performed in plants including rice (Ribeiro *et al.*, 2016) and
51 *Populus* (Sun *et al.*, 2019) have contributed to an improved understanding of these gene-function
52 relationships and others.

53 GWAS of root traits, both from adventitious roots and non-adventitious roots, commonly
54 involve measurement of the lengths, diameters, or types of roots, among other statistics. As
55 collection of these traits can prove laborious and time-consuming, a wide array of computer
56 vision tools have been developed to extract these features from root images, with varying
57 degrees of human intervention or automation (e.g., Arsenault *et al.*, 1995; Das *et al.*, 2015;
58 Zhang *et al.*, 2018; Yasrab *et al.*, 2019; Zheng *et al.*, 2020). These methods have been applied to
59 enable GWAS and other genetic analyses of rooting in common bean, cowpea (Burridge *et al.*,
60 2016), maize (Arsenault *et al.*, 1995; Zhang *et al.*, 2018) and hybrid poplar (Sun *et al.*, 2019),
61 among others. Methods involving manual measurements with rulers or ImageJ have been applied
62 to GWAS of rooting traits in plants including maize (Trachsel *et al.*, 2011), rice (Courtois *et al.*,

63 2013; Li *et al.*, 2017; Wang *et al.*, 2018; Xu *et al.*, 2020; Zhang *et al.*, 2020), wheat (Ayalew *et*
64 *al.*, 2018) and hybrid poplar (Dash *et al.*, 2018). The production of more general and user-
65 friendly root phenotyping platforms can help to extend automated methods to more species and
66 laboratories, potentially assisting expansion of GWAS population size by reducing the amount of
67 manual labor needed for phenotyping. With increased population size, GWAS gain greater
68 statistical power and improved ability to detect significant effects of genes regulating traits,
69 particularly those of smaller effect size, and those imparted by rare alleles (López-Cortegano &
70 Caballero, 2019).

71 Here, we report insights into the genetic control of rooting obtained through GWAS. By
72 use of a large resequenced and highly polymorphic population of wild *Populus trichocarpa* that
73 shows very rapid decay of linkage disequilibrium—and a novel machine vision phenomic system
74 and multiple GWAS pipelines—we were able to statistically detect large numbers of candidate
75 genes. The potential for rare allele discovery was enhanced by our use of the SNP-Set Sequence
76 Kernel Association Test, which upweights and combines effects from rare SNPs to increase
77 power in their detection (Wu *et al.*, 2011). We report a total of 277 unique associations passing
78 significance thresholds, including many involved in hormone signaling, cell division, and post-
79 translational modification of proteins—in addition to many genes of unknown function.

80 **Methods and Materials**

81 Plant materials

82 We used a *P. trichocarpa* GWAS population that was recently expanded to include a
83 total of 1,323 genotypes (Yates *et al.*, 2021); subsets of this population were used in previous
84 GWAS projects (Tuskan *et al.*, 2018; Bdeir *et al.*, 2019; Weighill *et al.*, 2019; Chhetri *et al.*,
85 2020; Chen *et al.*, 2021; Nagle *et al.*, 2022). This population is comprised of variation in wild *P.*
86 *trichocarpa* spanning regions of British Columbia, Washington, Oregon, Idaho and northern
87 California. Clone banks for this GWAS population were produced in multiple locations, among
88 which a replicate in a Corvallis, OR field location was utilized to obtain cuttings for this study.
89 This study was performed using materials collected as described in previous work (Nagle *et al.*,
90 2022). In summary, dormant cuttings were collected in the winters of 2018, 2019 and 2020, then
91 rooted up to a year later and grown in a greenhouse. Finally, fresh cuttings were collected and
92 frozen for 2-4 weeks, then used for rooting assays.

93 Assay of rooting

94 Cuttings were placed in 50mL Falcon tubes with water and allowed to root. Beginning
95 two weeks later, images were collected at weekly timepoints for four weeks. Prior to taking each
96 image, plants were removed from water and placed on top of a surface with roots arranged to
97 separate putative lateral and basal roots. To aid their recognition by our machine vision pipeline,
98 basal roots were laid downward atop blue felt while lateral roots were laid to the side on gray
99 felt. Each image also included a label and ruler. Plants were imaged from above using a Canon
100 Rebel XSi DSLR camera attached to a mount and facing downward. Due to practical limitations
101 in the number of cuttings that could be studied at once, the study was divided into eight
102 “phases,” each of which featured ~400 cuttings, including two replicates for each of ~200 given
103 genotypes.

104 Computer vision pipeline

105 We adopted the DeepLab network (Chen *et al.*, 2018) with backbone ResNet50 (He *et*
106 *al.*, 2016) as our segmentation model for its efficiency and accuracy. We trained two different
107 segmentation models: the first was used to segment an image into background, plant, ruler, and
108 label (Model 1); the second was used to segment the image into background, leaf, stem, and root
109 (Model 2). Below, we introduce how we collected training labels to train the two networks and
110 then used the two networks to measure biological traits of interest.

111 Because images were collected in various orientations, with the camera in either portrait
112 or landscape mode, we first rotated images to a uniform orientation. Next, the background was
113 segmented based on color thresholding. As the plant, ruler and label varied in color and were
114 found in approximately similar positions from image to image, we first segmented these
115 components based on their spatial positioning and colors using mean-shift segmentation and k-
116 means clustering. Images successfully segmented as such were used to produce a training set
117 with approximately 500 images used to train a deep model for segmentation of the remaining
118 images. Inference was performed using this model, and correct examples were used to retrain the
119 model with an expanded dataset, resulting in a final model trained with 2,239 examples (Deep
120 Model 1). Afterward, to segment the plant into stem, root and leaf, we performed mean-shift
121 segmentation and applied a location threshold to produce a training set of approximately 900
122 images. These were used to train a second deep model and the training set was again expanded

123 by running inference on new images and selecting correct results, resulting in a final training set
124 with 3,496 training examples (Deep Model 2).

125 Following training of both deep segmentation models, they were applied for inference of
126 the full dataset. All images were standardized to the same orientation, followed by deployment of
127 both models. The final result of segmentation was separation of background, leaf, stem, root,
128 ruler, and label for each image. Next, the segmentation results were further analyzed to produce
129 statistics on biological traits of interest. Since the camera height varied across images, we
130 computed the number of pixels per ruler width for each image to enable standardization via the
131 actual size represented by a single pixel.

132 We proceeded to compute the lengths and area of roots in centimeters, as well as the
133 diameters of stems. Root statistics were computed as follows. (1) First, we isolated the segment
134 of root by distinct connections to the stem via connected components (2) The background was
135 classified as top background and bottom background based on the color of the felt background
136 below the stem, allowing each root to be classified as lateral or basal depending on the
137 background. (3) For each basal and lateral root, we computed root length using a distance map
138 and root area by counting pixels. Longest root length (LRL) and total root area were computed
139 separately for basal and lateral roots in each image. RGB and false-color images of the
140 segmentation process are shown in Fig. 1.

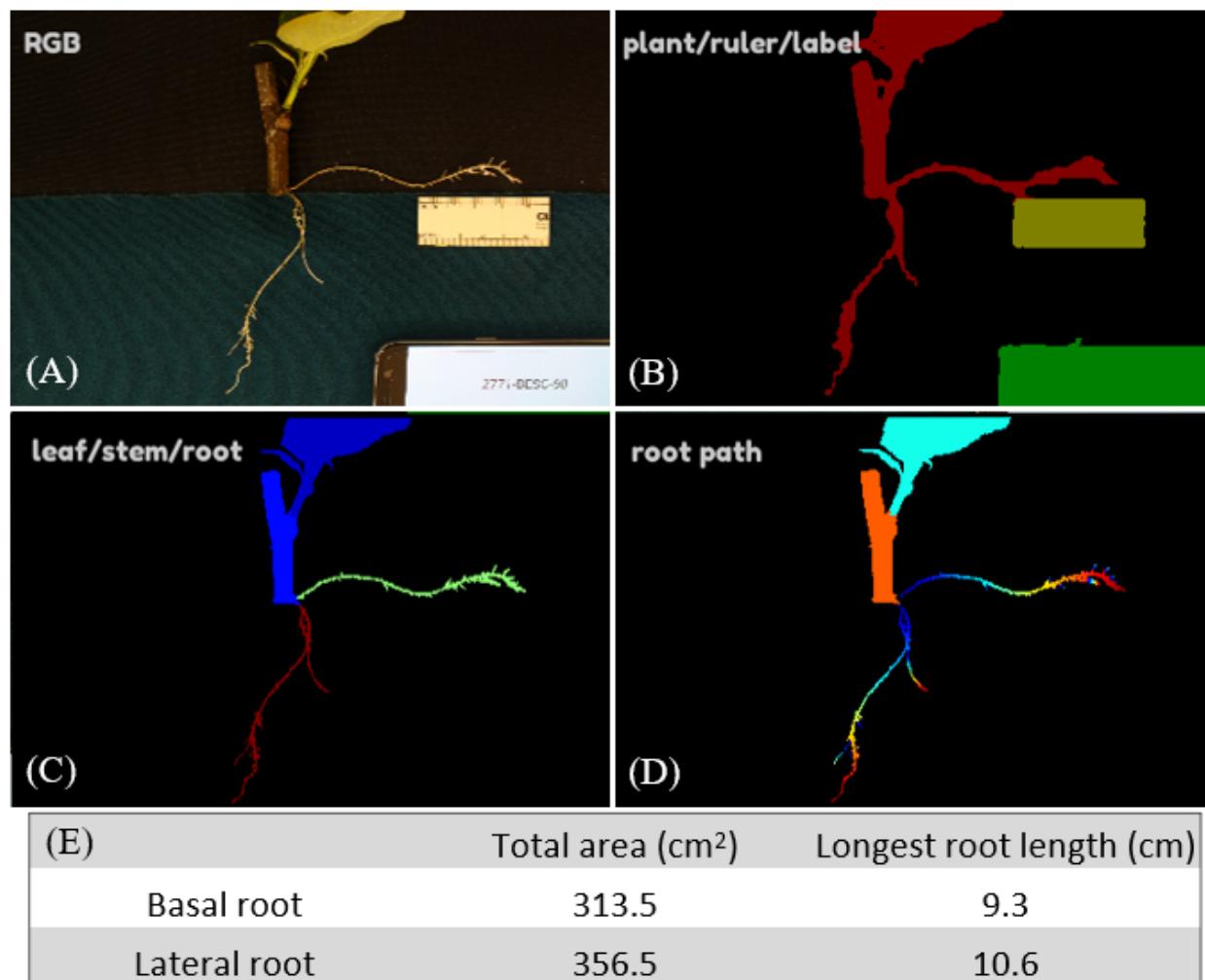


Figure 1. Workflow for phenotyping root traits: (A) RGB images were collected for plants with rulers and labels. (B) The first round of segmentation was performed to separate the plant, ruler and label. (C) A subsequent round of segmentation separated the roots by their type (basal or lateral, shown respectively in red and green). (D) Finally, the length of each root was measured from root tip to connection to stem. (E) An example of total area and longest root length computed over basal and lateral types of adventitious roots.

141 Data Error Checking Methods

142 Source images were compared to segmented images (e.g. Fig. 1) to identify cases where
143 data contained errors for the length, area, type or number of roots. Each image was scored
144 according to the error or errors observed (Table 1). Images were then sorted into folders

145 according to the types of data errors they contained using a spreadsheet and an R script.

146

Error ID	Description	Frequency among images
0	No significant error	81.3%
1	Undetected roots	1.3%
2	Incorrect number of roots	7.2%
3	Undetected basal root, but detected lateral root	0.2%
4	Incorrectly identified feature (e.g. basal root labeled as lateral)	4.6%
5	Root label shorter than root in image (truncation)	2.9%
6	Errant detection of root where no root exists	0.3%

Table 1. Descriptions of error types and their frequencies

147 Data Correction Methods

148 ImageJ version 1.53a software and the SmartRoot version 4.21 plugin were installed and used to
149 make all measurements. Source images were opened in ImageJ with the SmartRoot plugin then
150 converted to an 8-bit greyscale and inverted. The global scale was then set to 1 pixel/unit in
151 ImageJ and 2.54 DPI in SmartRoot to acquire units of pixels for all measurements. Roots that
152 required correction of length data were then traced using the SmartRoot Trace Root tool. To
153 calculate root areas, the image color threshold was adjusted until only the roots were highlighted,
154 then the area was selected using the Wand Tracing tool and measured in ImageJ. Root types
155 were corrected based on manual judgement of whether a root was a lateral root or basal root,
156 while recalling that these were placed on different areas of felt during imaging as previously
157 described.

158 Data preparation

159 Mean values of each trait were computed across replicates for each genotype and used for
160 downstream GWAS. Principal component analysis (PCA) was performed using `stats::princomp`
161 in R to produce PCs representing trends across traits and timepoints. PCA was performed over
162 three batches of traits: 1) area of basal or lateral roots at all timepoints; 2) LRL for basal or
163 lateral roots at all timepoints; and 3) all traits, including area and LRL of basal or lateral root at
164 all timepoints. Scree plots were consulted to determine the numbers of PCs, representing
165 significant variation for each batch, to be used for downstream GWAS.

166 Normality of traits was assessed in parallel to traits for our published GWAS of *in planta*
167 regeneration in poplar, using the same methods (Nagle *et al.*, 2022). In short, we assessed
168 normality of untransformed traits using Q-Q plots, histograms, Shapiro-Wilks tests and Pearson
169 correlation coefficients with theoretical normal distributions, then applied necessary
170 transformations including Box-Cox transformations, rank-based inverse normal transformations,
171 removal of zero values and removal of outliers on a case-by-case basis for conservative but
172 adequate transformation of each trait (Figure S2, Table S1-2).

173 Association mapping

174 Association mapping of all traits was performed in parallel with traits in our published
175 GWAS of *in planta* regeneration, using methods and SNP sets detailed in this previous work
176 (Nagle *et al.*, 2022). To summarize, four GWAS methods were used: 1) Genome-wide Efficient
177 Mixed Model Association (GEMMA; Zhou & Stephens, 2012); 2) Generalized Mixed Model
178 Association Test (GMMAT; Chen *et al.*, 2016); 3) Fixed and Random Model Circulating
179 Probability Unification (FarmCPU; Liu *et al.*, 2016), specifically the implementation
180 FarmCPUp (Kusmec & Schnable, 2018); and 4) SNP-set (sequence) Kernel Association Test
181 (SKAT; Ionita-Laza *et al.*, 2013) with the Multi-Threaded Monte Carlo SKAT (MTMC-SKAT)
182 R extension we developed. Versions of trait data transformed toward normal distributions were
183 analyzed with GEMMA and FarmCPU, while binarized traits were analyzed with GMMAT and
184 untransformed traits with MTMC-SKAT using resampling to avoid violations of linear model
185 assumptions for high-confidence associations. GEMMA and GMMAT were run using kinship
186 matrices to adjust for population stratification, with a set of 13.2 million SNPs with a minor
187 allele frequency (MAF) threshold of 1% and that are missing in no more than 10% of genotypes.
188 FarmCPU uses a novel approach to adjust for population stratification while avoiding
189 overcorrection and was run with a SNP set with MAF above 5%, missing rate below 10% and
190 pruning based on linkage disequilibrium (LD). MTMC-SKAT was run using six principal
191 components derived from SNP data to correct for population stratification and a set of 34.0 M
192 SNPs with missing rate below 15%. MTMC-SKAT was deployed on the high-performance
193 cluster COMET, made available through NSF XSEDE (Towns *et al.*, 2014). Stem diameter and
194 phase were used as covariates for all GWAS methods.

195 To identify QTLs from results that are statistically significant, we computed multiple
196 testing correction thresholds using the Bonferroni method (parameters: $\alpha = 0.05$, N tests equal to

197 N SNPs) and Benjamini-Hochberg false discovery rate ($\alpha = 0.10$). We further sought to identify
198 candidate genes that failed to meet significance according to either of these criteria, but were
199 represented by a peak of QTLs showing a pattern of LD decay suggestive of a causative
200 association. Toward this end, we applied an implementation of the Augmented Rank Truncation
201 (ART; Vsevolozhskaya *et al.*, 2019) over GEMMA and GMMAT results as we previously
202 described (Nagle *et al.*, 2022).

203 **Results**

204 Principal components describe complex patterns of root development

205 Significant patterns of root development over time and across root types (basal and
206 lateral) were summarized by PCA. For each of the three batches of traits used for PCA, the top
207 two PCs appear to explain significant portions of variance as indicated by Scree plots. PCA was
208 performed over three batches as previously described (Methods and Materials). The first two
209 batches, for root area or root length traits, each across basal and lateral roots and timepoints, both
210 produced a first PC representing lateral root development independent of basal root and a second
211 PC representing a lack of basal root development independent of lateral root (Fig. 2, Fig. S1).
212 For the third batch, including all area and length traits together, the first PC shows a trend of
213 overall root development and the second shows a preference for development of basal root rather
214 than lateral root (Fig. S2).

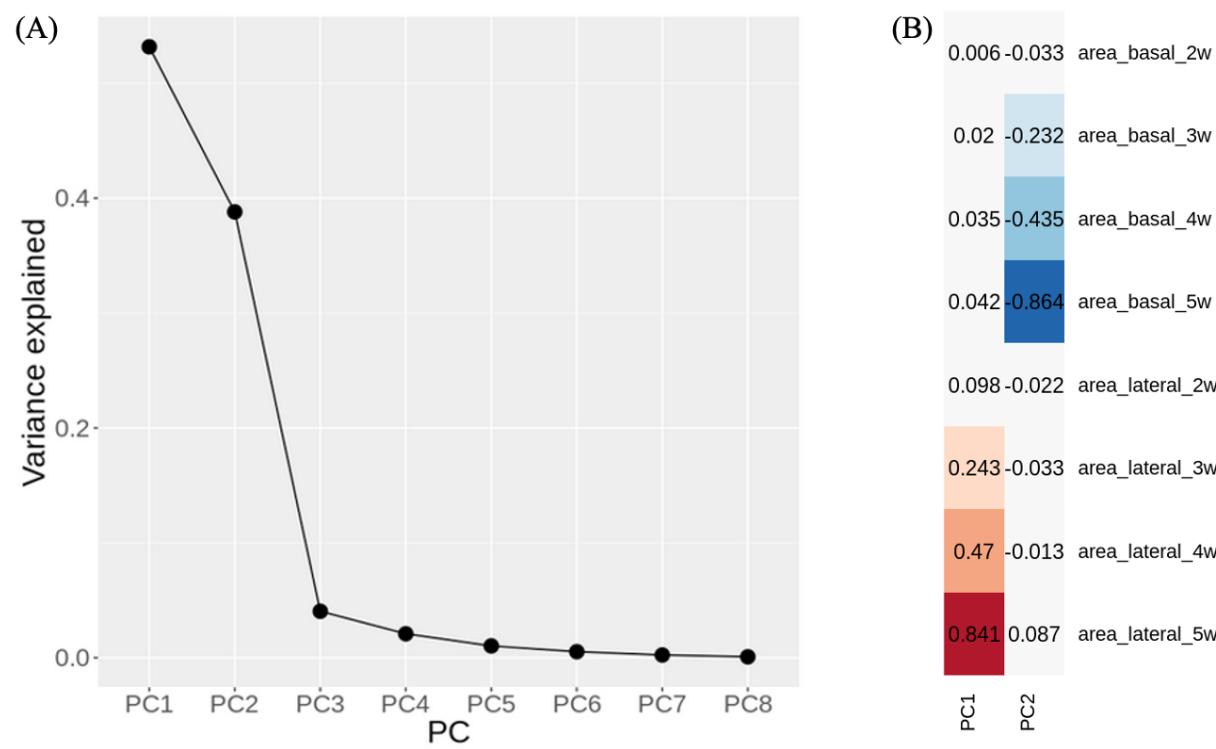


Figure 2. Results from PCA over all root area traits, across root type (basal or lateral) and all four timepoints of data collection: (A) Scree plot showing proportion of variance explained by each PC; (B) Loadings for top two PCs.

215

216 Use of multiple GWAS methods yielded numerous associations

217 We evaluated results to identify candidate QTLs and genes implicated for all 13 traits with h^2_{SNP}
218 above 0.10, three of which were evaluated with two different transformations due to ambiguity in
219 the ideal transformation (Table S1-S3). We term a “QTL peak” as any SNP or SNP window
220 associated with a given trait that is not within 30kb of any other SNP or SNP window with a
221 lower p -value for the associated trait, thus appearing as the peak position of a group of signals on
222 a Manhattan plot. Only MTMC-SKAT yielded QTL peaks passing the conventional Bonferroni
223 threshold under the assumption that each test (SNP window) is independent. MTMC-SKAT
224 using 3kb SNP windows yielded a total of 31 unique Bonferroni-significant associations across
225 all traits, 22 of which had a window center within 5kb of an annotated gene, as well as 164
226 unique associations passing the FDR ($\alpha = 0.10$) and/or the conservative Bonferroni threshold
227 (112 of which had window centers within 5kb of a gene). The apparent power of SKAT is in

228 contrast to GEMMA and GMMAT; GEMMA yielded only two associations passing the FDR (α
229 = 0.10) threshold and none passing the conservative Bonferroni threshold, while GMMAT
230 yielded none passing either. Statistical power for GEMMA and GMMAT was greatly increased
231 by the use of ART to combine signals across windows of SNPs, which enabled detection of over
232 100 associations for GEMMA and eight for GMMAT (Fig. 3-4). Fig.5 provides an example of
233 manual inspection of QTL peaks using integrative genomics viewer (IGV; Thorvaldsdóttir *et al.*,
234 2013). Associations of note that are addressed in the discussion section are presented in Table 2,
235 with summary statistics for all associations in Table S4 and details presented in Table S5-8. No
236 significant associations were found using FarmCPU.

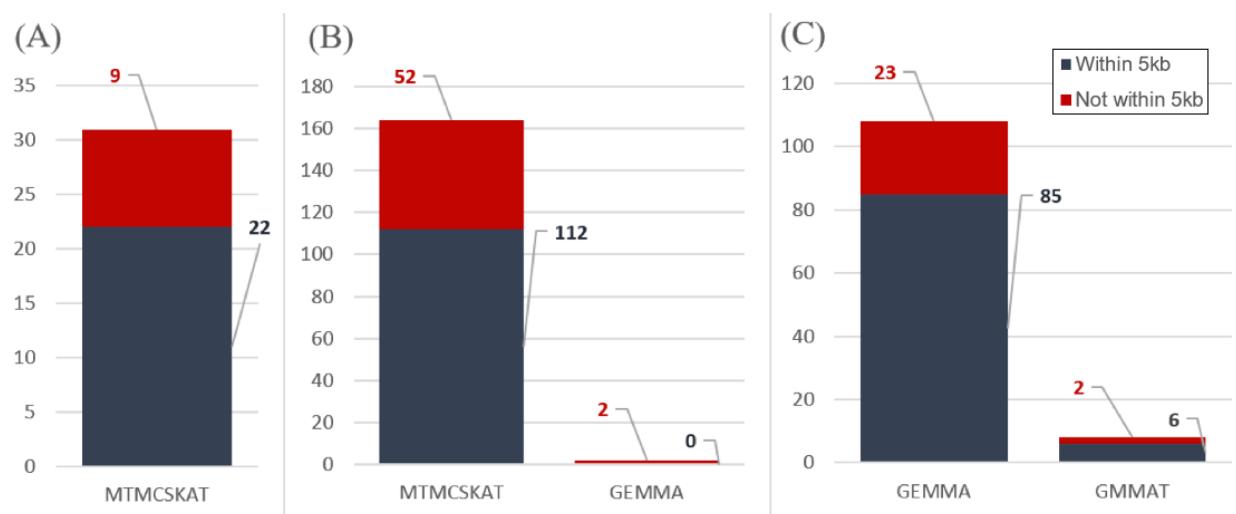


Figure 3. Barplots summarizing the numbers of associations from each GWAS method, with each type of significance threshold, as well as within a 5kb distance threshold to the nearest gene. QTL peaks were taken as the point with the lowest p -value at any given position near a significant SNP, where multiple points within the same peak may otherwise pass a given significance threshold. (A) QTL peaks passing the conservative Bonferroni threshold, given an assumption of independence of all SNP associations; (B) QTL peaks passing Benjamini-Hochberg threshold (FDR; $\alpha = 0.10$) and/or the conservative Bonferroni Threshold. (C) QTL peaks passing ART-Bonferroni threshold ($\alpha = 0.05$, N of # 1kb windows in genome); ART was only applied to the single-SNP GWAS methods, GEMMA and GMMAT.

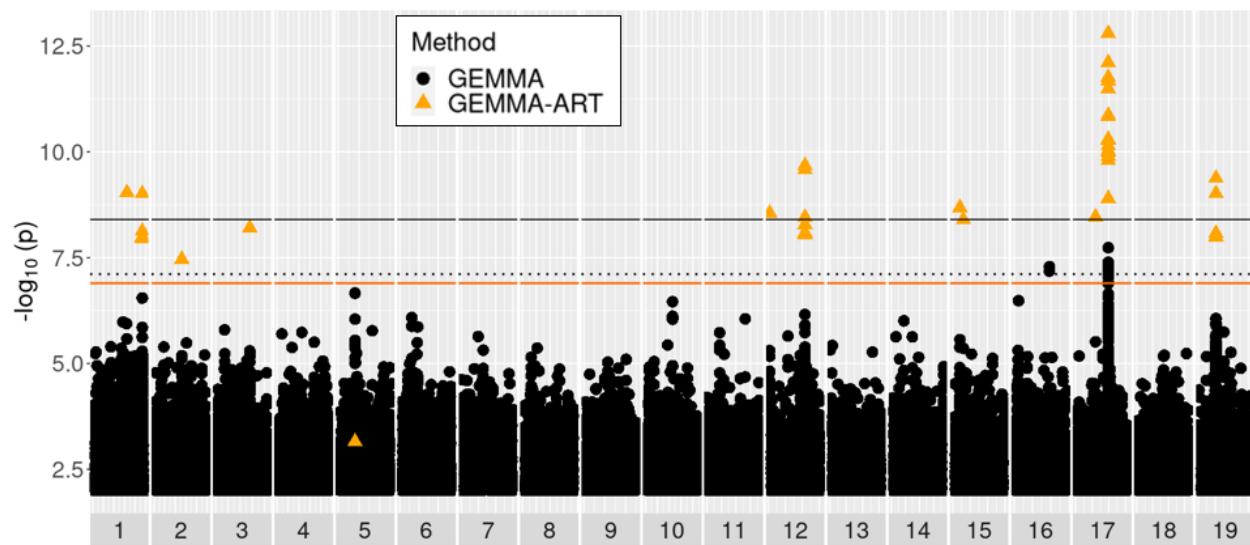


Figure 4. Manhattan plot of GEMMA results for the trait of longest lateral root length at week 3. Black and orange solid lines represent Bonferroni significance thresholds for GEMMA results with independent SNPs, and for ART applied to GEMMA over 1kb windows of SNPs. The black dotted line represents the significance threshold with a false discovery rate of 10% for independent SNP tests. Black circles represent tests of individual SNPs by GEMMA. Orange triangles represent 1kb windows tested by ART applied to GEMMA results.

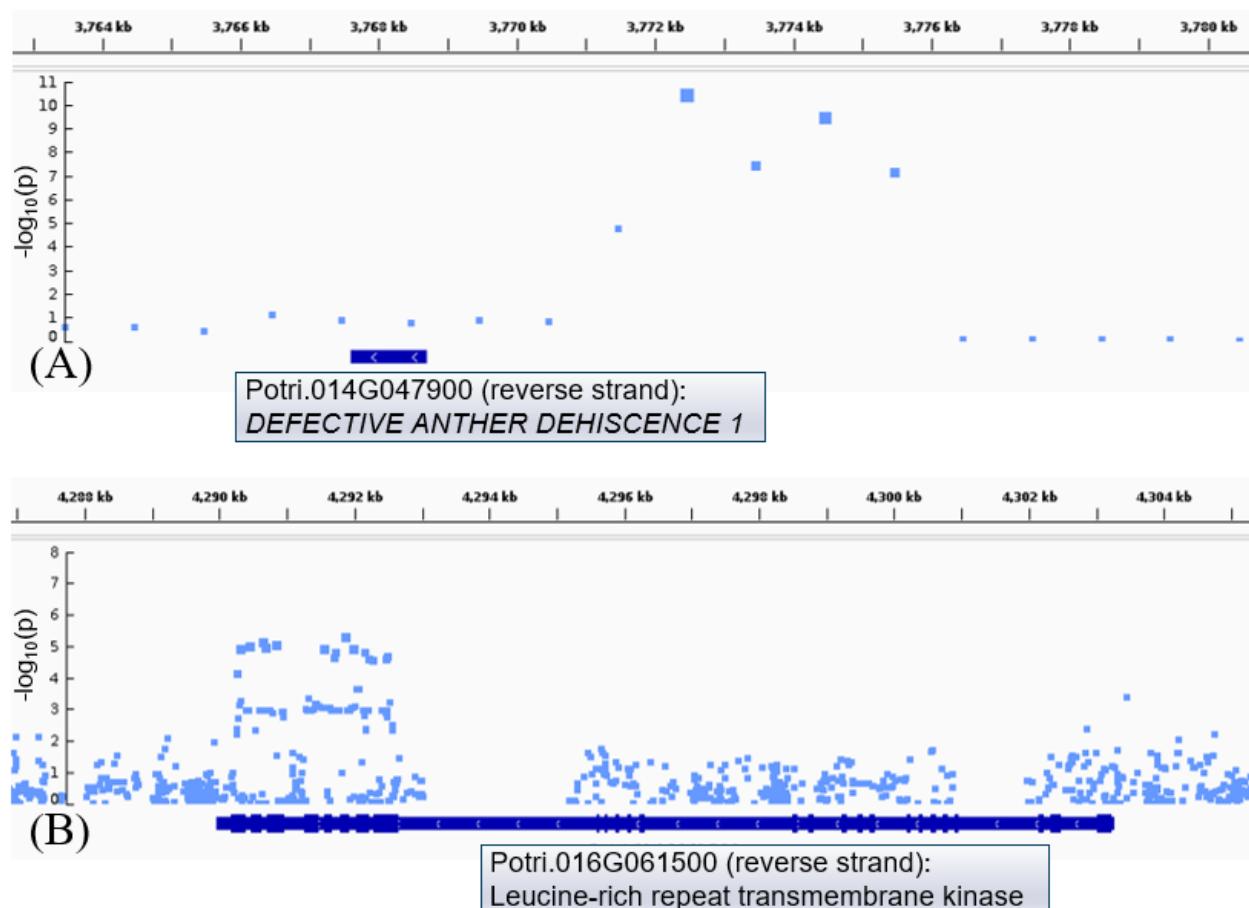


Figure 5. Close-up view of Manhattan plots aligned with *P. trichocarpa* genome annotation (v3.1) using IGV. (A) SKAT results (prior to resampling top associations with MTMC-SKAT) for LRL at week three display an association with a possible promoter region of a putative homolog of *DEFECTIVE ANTER DEHISCENCE 1*; (B) GEMMA results (without GEMMA-ART displayed) for basal root area at week five display an association with a ~2kb region of exons and short introns of a putative leucine repeat rich transmembrane protein kinase. Exons are visualized as thickened portions on the gene track. Plots are displayed without MTMC-SKAT and GEMMA-ART *p*-values for simplicity; these statistics can be found in Table S6-7. Boxes with gene accession IDs, strand of gene and gene info were added manually to IGV plots.

Gene candidates							Arabidopsis homologs			
Threshold	Trait name	Method	Transformation	Dist.	QTL Pos.	Accession ID	Description	Accession ID	Score	Similarity
Bonf.	RA PC2	MTMC-SKAT	Untransformed	3,509	Intragenic, non-exonic	Potri. 001G149200	novel plant snare 11	AT 2G35190	403	92.3%
Bonf.	RA PC2; Basal RA growth wk. 2-5; Basal RA wk. 5	MTMC-SKAT	Untransformed	2,034	5'	Potri. 003G054300	lincRNA	NA	NA	NA
FDR ($\alpha = 0.1$)	Overall PC2	MTMC-SKAT	Untransformed	22	3'	Potri. 004G210600	FASCICLIN-like arabinogalactan-protein 12	AT 5G60490	189	83.0%
Bonf.	RA PC1	MTMC-SKAT	Untransformed	52	5'	Potri. 005G141900	CYCLIN D3;2	AT 5G67260	361	74.9%
Bonf.	RA PC2; Basal RA growth wk. 2-5; Basal RA wk. 5 Lateral	MTMC-SKAT	Untransformed	730; 270	5'; Intragenic, non-exonic	Potri. 006G161200	indoleacetic acid-induced protein 16	AT 3G04730	162	86.0%
Bonf.	LRL (wk. 3)	MTMC-SKAT	Untransformed	596	5'	Potri. 006G193400	lincRNA	NA	NA	NA
Bonf.	RA PC2; LRL PC2; Basal RA growth (wk. 2-5); Basal RA (wk. 5); Overall PC2	MTMC-SKAT	Untransformed	1,570; 2,570	Exonic	Potri. 007G056400	histidine kinase 1	AT 2G17820	1634	81.8%
Bonf.	RA PC1	MTMC-SKAT	Untransformed	10,480; 11,480	5'	Potri. 010G031800	Protein kinase family protein	AT 5G18700	1828	81.7%

FDR ($\alpha = 0.1$)	LRL PC2	MTMC-SKAT	Untransformed	4,967	5'	Potri. 011G028200	with ARM repeat domain				
Bonf.	LRL (wk. 3)	MTMC-SKAT	Untransformed	3,775; 5,775	5'	Potri. 014G047900	cysteine-rich RLK (RECEPTOR-like protein kinase) 25	AT 4G05200	393	65.1%	
Bonf.	RA PC1	MTMC-SKAT	Untransformed	2,296	5'	Potri. 015G105000	DEFECTIVE ANTHER DEHISCENCE 1	AT 2G44810	560	88.0%	
Bonf.	LRL (wk. 3)	MTMC-SKAT	Untransformed	1,181; 2,181	3'	Potri. 017G083100	dual specificity protein phosphatase family protein	AT 5G23720	1189	81.8%	
Bonf.	RA PC1	MTMC-SKAT	Untransformed	913; 87	3'; Exonic	Potri. 018G097000	lincRNA	NA	NA	NA	
Bonf.	RA PC1	MTMC-SKAT	Untransformed	1,437; 2,437	3'	Potri. 019G127200	Fasciclin-like arabinogalactan family protein	AT 3G46550	394	82.7%	
ART-Bonf.	Lateral LRL (wk. 3)	GEMMA	Box-Cox	1,165	5'	Potri. 001G436800	Protein kinase family protein with leucine-rich repeat domain	AT 1G35710	893	68.9%	
ART-Bonf.	RA PC2	GEMMA	Outliers removed, RB-INV	2,242	5'	Potri. 004G023100	glutathione S-transferase TAU 25	AT 1G17180	308	80.7%	
ART-Bonf.	RA growth (wk. 2-5)	GEMMA	Box-Cox	896	5'	Potri. 010G202000	Peroxidase superfamily protein	AT 3G01190; AT 5G15180	407; 403	75.4%; 75.8%	
ART-Bonf.	Lateral LRL (wk. 3)	GEMMA	Box-Cox	1,753	5'	Potri. 012G081500	actin-related protein 5	AT 3G12380	1113	87.3%	
							ataxia-telangiectasia mutated	AT 3G48190	350	58.8%	

ART-Bonf.	Basal RA (wk. 5)	GEMMA	Box-Cox	0	Exonic	Potri. 016G061500	Leucine-rich repeat transmembrane protein kinase	AT 1G53440	622	62.7%
ART-Bonf.	RA growth (wk. 2-5)	GMMAT	Binarized trait	2,675	5'	Potri. 008G072700	ferritin 2; ferritin 4	AT 2G40300	373; 358	83.1%; 84.9%

Table 2. Twenty gene candidates with *Arabidopsis* homologs or encoding lincRNAs with putative role in biological processes of root development. For each candidate with an *Arabidopsis* homolog, relevant literature is summarized (Discussion). QTLs were identified from various traits related to root area (RA) and longest root length (LRL), for either basal or lateral ARs, or both types combined. For some associations found by MTMC-SKAT, two nearby SNP windows have equal *p*-values for association ($1*10^{-7}$) due to the practical limits of our permutation analysis. Remaining associations are presented in Tables S5-S8.

237 **Discussion**

238 As discussed in depth below, we reported a high number of putative associations from our
239 GWAS pipeline. FarmCPU, however, gave no significant associations, and only a single
240 candidate association in our prior study using this pipeline (Nagle *et al.*, 2022). We are unaware
241 of any other reports of this GWAS method being used in poplar. We speculate that the lack of
242 success with this method may stem from the high SNP density and rapid linkage disequilibrium
243 (LD) decay in poplar, the unique approach FarmCPU employs in controlling for population
244 stratification using a limited set of SNPs, and/or the LD-based pruning that was needed to avoid
245 errors during this process for the SNP set we used.

246 Two putative modes of adventitious root regeneration in poplar

247 We observed that when ARs grew from the base of cuttings, the base was often enlarged,
248 distorted, and disorganized in appearance, resembling the calli found in *in vitro* tissue cultures or
249 at *in planta* wound sites (Fig. 6). We term these “basal ARs.” Although we are aware of little
250 research into this specific type of AR in poplar, research in *Populus balsamifera* (a closely
251 related species interfertile with *P. trichocarpa*), suggested that AR development depends on
252 calcium and pH, and that hard callus may inhibit root emergence (Cormack, 1965). More
253 recently, basal ARs growing from callus have been studied in *Pinus* (Rasmussen *et al.*, 2009).
254 These contrast with ARs growing from the sides of cuttings (“lateral ARs”), which appeared to
255 grow directly from the stem without an intermediate callus stage (Fig. 6). Prior histological
256 research in poplar indicated that lateral ARs appear to originate from secondary meristematic
257 tissue in the cambium (Rigal *et al.*, 2012). We therefore set up our phenomics pipeline to
258 measure lateral and basal ARs separately, assuming they are biologically distinct and likely
259 originate from different progenitor cells. Their high degree of independence was supported by
260 our PCA analysis, which by inspection of loadings appear to represent “ratios” between the two
261 types of root (Fig. 2, Fig. S1-2). There was also a number of GWAS associations for one root
262 type or the other, or for these PCs (discussed below).



Figure 6. Selected images collected during root phenotyping, with zoomed-in views showing callus or callus-like tissue at the base of stems from which basal ARs emerge. (A) Genotype BESC-153, (B) BESC-327, (C) GW-9914, and (D) BESC-337.

263

264 Phenomics workflow accelerated phenotyping but required human intervention

265 Our phenomics workflow using machine vision enabled us to extract root trait data from
266 a number of images that would otherwise have been infeasible for humans unassisted. The
267 training of models for this workflow did not require manual preparation of ground-truth semantic
268 labels by humans using an annotation interface, but rather utilized ground-truth labels prepared
269 by thresholding and cropping. Although this approach offers the advantage of accelerated
270 training dataset preparation, it lacks the ability for machine vision results to be compared to

271 human-produced ground truth labels using statistics such as intersection over union (IoU). To
272 assess model performance, we inspected each image and grouped them according to notable
273 errors that we observed. The most frequent errors were in root counting, found in at least 7.2.%
274 of images (Table 1). Root count statistics were not used in GWAS because of the relatively high
275 error rate and because the summary statistics of aggregate root area provides a proxy for root
276 system proliferation, while being more robust to errors. Another common type of error was of
277 incorrectly applied labels, for example basal roots labeled as lateral roots or vice versa (Table 1).
278 With our system, we attempted to facilitate the labeling of basal and lateral roots by manually
279 placing roots of each type in areas with different background colors (Fig. 6). We are not aware of
280 other root phenomics workflows that aim to distinguish basal and lateral ARs, although several
281 distinguished root type for non-adventitious roots, such as for alfalfa (Xu *et al.*, 2022),
282 Arabidopsis, wheat and *Brassica* (Yasrab *et al.*, 2019).

283 We attempted to correct errors using ImageJ with the SmartRoot plugin (Methods and
284 Materials). This error correction was performed on approximately 18.7% of images. Considering
285 our hybrid approach utilizing both machine vision and manual correction of errant labels, our
286 method is comparable to RootReader (Clark *et al.*, 2013), a tool that similarly performs initial
287 labeling of images and then allows for user correction. The scope of our work did not include the
288 development of a user-friendly and generalizable root annotation method that can be practically
289 applied by other labs with diverse imaging conditions and across diverse species of plants.
290 However, several such tools have been recently developed, including RootNav 2.0, which has
291 demonstrated an ability via transfer learning to generalize across different background types and
292 species including maize, Arabidopsis and *Brassica* (Yasrab *et al.*, 2019).

293 Gene candidates represent diverse functional roles

294 *Regulators of cell division and structure*

295 D-type cyclins regulate the G1-to-S progression of the cell cycle and comprise a family
296 of ten known proteins in Arabidopsis and 22 in poplar (Dong *et al.*, 2011). Potri.005G141900
297 encodes a homolog of CYCLIN D3;2 (CYCD3;2) or CYCLIN D3;3 (CYCD3;3), which are
298 among at least five D-type cyclins known to have roles in root precursor cells in embryonic
299 and/or mature tissues (De Veylder *et al.*, 1999; Nieuwland *et al.*, 2009; Collins *et al.*, 2012;
300 Forzani *et al.*, 2014). A comparative transcriptomic study in *Populus* found this gene to be
301 differentially expressed between two genotypes with contrasting rates of stem growth and

302 biomass accumulation (Han *et al.*, 2020). In *Arabidopsis*, concurrent knockout of all three
303 members of the CYCD3 clade led to retarded seed development, while overexpression of
304 CYCD3;1 led to premature, irregular and disorganized division of the hypophysis (Collins *et al.*,
305 2012). Transcription of CYCD3;1 and CYCD3;3 is negatively regulated by WUSCHEL-
306 ASSOCIATED HOMEOBOX 5 (Forzani *et al.*, 2014), a poplar homolog of which enhances AR
307 in poplar when overexpressed (Li *et al.*, 2018). Although we are unaware of any reports of
308 mutant phenotypes resulting from CYCD3 overexpression or knockout in mature roots, several
309 relevant root-related phenotypes have been reported for CYCD2 and CYCD4 members.
310 CYCLIN D4;1 knockout was reported to reduce pericycle cell divisions as well as the number of
311 lateral roots, while these phenotypes were rescued by exogenous auxin, perhaps due to auxin-
312 responsiveness of D-type cyclins with overlapping functional roles (Nieuwland *et al.*, 2009).
313 CYCD2;1 overexpression led to increased root apical meristem divisions and increased
314 sensitivity to effects of exogenous auxin in promoting lateral root formation, while knockout led
315 to reduced auxin sensitivity although no reduction in RAM divisions, possibly due to redundant
316 homologs (Sanz *et al.*, 2011).

317 Potri.001G149200 encodes a homolog of NOVEL PLANT SNARE 11 (NPSN11), which
318 is believed to interact with other SNARE proteins to provide energy needed for the fusion of
319 membranes that give rise to the cell plate during cytokinesis (Zheng *et al.*, 2002). Knockout of
320 NPSN11 alone yields no mutant phenotype in *Arabidopsis*, putatively due to redundancy with a
321 similar SNARE protein. Defects in cytokinesis and embryo development are conferred by
322 simultaneous knockout of NPSN11 and the functionally redundant SNAP33 (El Kasmi *et al.*,
323 2013).

324 Potri.004G210600 and Potri.018G097000 encode members of the FASICLIN-LIKE
325 ARABINOGALACTAN (FLA) family, which consists of 21 members in *Arabidopsis* and has
326 established roles in adhesion in cell walls, plasma membranes and extracellular matrices
327 (reviewed by Zang *et al.*, 2015). Transcriptomic analysis of tension wood development in
328 *Populus* provides support for a role of Potri.004G210600 in cell wall structure (Bygdell *et al.*,
329 2017). Knockout of *Arabidopsis* FLA4, also known as SALT OVERSENSITIVE 5, was reported
330 to reduce root elongation, cell wall thickness and root tip swelling under salt stress (Shi *et al.*,
331 2003) and experiments with ethylene inhibitors suggest that FLA4 functions downstream of

332 ethylene signaling (Xu *et al.*, 2008). We are unaware of reports of root-related mutant
333 phenotypes of other FLA members.

334 Cell expansion is influenced by bundling and rearrangements of actin filaments, regulated
335 at least in part by auxin and cytokinin (Zhu & Geisler, 2015; Scheuring *et al.*, 2016; Arieti &
336 Staiger, 2020). We report two gene candidates encoding putative actins or actin-like proteins,
337 Potri.010G202000 and Potri.012G081500. In *Arabidopsis*, loss-of-function mutants of ACTIN 7
338 displayed reduced root length and reduced cell divisions in the proximal meristem (PM) of root
339 tips as well as an increased number of transition zone (TZ) cells, while dual mutants of ACTIN 2
340 and ACTIN 8 presented a loss of root hairs and increases in TZ cells with a lack of PM effects
341 (Kandasamy *et al.*, 2009; Takatsuka *et al.*, 2018). The variable effects of different auxins on root
342 development, together with the lack of clear homology for these actin-related gene candidates,
343 welcome physiological investigation of the mechanisms by which these gene candidates may
344 affect root in poplar.

345 *Regulators of hormone signaling*

346 Potri.006G161200 encodes a member of the Aux/IAA F-Box protein family, believed to
347 have 35 members in *Populus trichocarpa* (Kalluri *et al.*, 2007) and 29 in *Arabidopsis*
348 (Overvoorde *et al.*, 2005), and appears to be a homolog of IAA16 or another member of the 29-
349 gene IAA family. In *Arabidopsis*, Aux/IAA proteins have been well-characterized and are known
350 to undergo auxin-dependent proteasomal degradation and to function via auxin-dependent
351 protein-protein interactions that repress the transcriptional activity of various Auxin Response
352 Factor (ARF) family members (reviewed by (Luo *et al.*, 2018)). A specific role for ARF
353 members in regulating AR development is believed to function via the action of downstream
354 *GRETCHEN HAGEN* family genes responsible for conjugating jasmonic acid (JA) into bioactive
355 jasmonoyl-L-isoleucine (JA-Ile). Evidence for conservation of this pathway in *Populus* has been
356 reported, with enhanced or delayed AR development respectively resulting from overexpression
357 or knockdown of a homolog of TRANSPORT INHIBITOR RESPONSE 1, responsible for
358 Aux/IAA proteasomal degradation and found to interact with a *Populus* homolog of IAA28 (Shu,
359 *et al.* 2019).

360 Further evidence for a role of JA signaling in rooting of poplar is indicated by an
361 association with Potri.014G047900, encoding a homolog of DEFECTIVE IN ANTER
362 DEHISCHENCE1 (DAD1), which catalyzes the first step of JA biosynthesis (Ishiguro *et al.*,

363 2001). Several possible roles for JA in adventitious rooting of *Populus* have been discussed in a
364 recent review; in summary, these roles may include cross-talk with auxin signaling among
365 others, and are evidenced to vary across genera (Bannoud & Bellini, 2021). Our previous GWAS
366 of *in planta* regeneration in poplar support a major role for JA signaling in callus and shoot
367 regeneration (Nagle *et al.*, 2022; and sources cited within), via pathways that are likely to be
368 relevant to adventitious rooting considering the previously discussed emergence of basal ARs
369 from callus.

370 *Regulators of post-translational modifications*

371 Among our candidate genes, we report a notable number of genes encoding putative
372 catalysts of post-translational modifications (PTMs), including a histidine kinase
373 (Potri.007G056400), serine/threonine kinases (Potri.011G028200, Potri.010G031800,
374 Potri.019G127200 and Potri.016G061500), a serine/threonine phosphatase (Potri.015G105000)
375 and a glutathione-S-transferase (Potri.001G436800). We are particularly unsure of the precise
376 mechanisms by which these candidates affect root traits because their PTM activity may be
377 highly nonspecific and a majority of plant genes are likely to undergo PTMs. Evidence has been
378 found for PTMs of over 12,000 substrates in *Arabidopsis* (Xue *et al.*, 2022), including
379 arabinogalactans (Schultz *et al.* 2004) and microtubule proteins involved in cell structure and
380 division (Parrotta *et al.*, 2014) as well as hormone signal regulators (reviewed by Hill, 2015).
381 Specific interactions between PTM catalysts and other gene candidates can be interrogated via
382 statistical tests for epistasis.

383 *Arabidopsis* mutants of certain PTM-related candidate homologs display phenotypes
384 relevant to root development. Mutants of the serine/threonine phosphatase PROPYZAMIND-
385 HYPERSENSITIVE 1 (homolog of Potri.015G105000) demonstrate embryo fatality (for null
386 mutants) or microtubule defects leading to left-handed helical growth of roots in seedlings (for
387 mutants with reduced phosphatase activity) (Naoi and Hashimoto, 2004). HISTIDINE KINASE
388 1 (homolog of Potri.007G056400) is believed to have a role in abscisic acid (ABA) signaling,
389 indicated by increased sensitivity of seedlings to the effects of ABA in inhibiting germination
390 (Tran *et al.*, 2007). In *Populus*, the putative histidine kinase Potri.007G056400 was found to be
391 differentially expressed in *Populus* roots in response to boron deficiency (Su *et al.*, 2019) and the
392 putative serine/threonine kinase Potri.015G105000 was previously identified in GWAS as an
393 association with bud set and growth period (McKown *et al.*, 2014).

394 *Noncoding RNAs*

395 We sought to identify possible targets of putative ncRNAs that were found as
396 associations in our GWAS, and indicated by the GreeNC pipeline to be probable ncRNAs
397 (Di Marsico *et al.*, 2022). Potri.003G054300 shares significant homology with the predicted
398 exon of Potri.006G260300, a gene that appears to encode a transmembrane protein but for which
399 we were unable to identify a homolog in model species. We did not find any known protein-
400 coding genes that Potri.006G193400 and Potri.017G083100 align well with. We note that
401 noncoding RNAs may be involved in processes other than RNA interference of coding genes,
402 such as in ribonucleoprotein complexes and chromatin modification (reviewed by Statello *et al.*,
403 2021). Whereas gene-silencing effects of ncRNAs can be predicted by sequence alignment, other
404 roles may not be unraveled without wet-lab protocols (reviewed by Lucero *et al.*, 2021).

405 *Regulators of reactive oxygen species (ROS) signaling*

406 ROS can affect or correspond to root development through multiple mechanisms. High
407 levels of ROS are associated with various biotic and abiotic stressors in plants (Sharma *et al.*,
408 2019; Qamer *et al.*, 2021) and are well-established as a cause of DNA and tissue damage across
409 eukaryotes (Arfin *et al.*, 2021). As a means of post-transcriptional regulation, ROS can catalyze
410 activation of deactivation of transcription factors (Wu *et al.*, 2012; Kong *et al.*, 2018) and other
411 developmental genes such as cell cycle regulators (Yi *et al.*, 2014). Additionally, the previously
412 discussed roles of auxin in root signaling relate to ROS as the bioactive auxin IAA is produced by
413 a peroxisome-mediated reaction involving the precursor IBA, producing nitric oxide as a
414 byproduct (reviewed by Damodaran & Strader, 2019). Moreover, nitric oxide is involved in
415 nitrosylation of proteins including the auxin receptor TRANSPORT INHIBITOR RESPONSE
416 (TIR1), promoting its interaction with Aux/IAA proteins (Terrile *et al.*, 2012) such as the
417 previously discussed IAA16. NO and ROS also have roles in mediating symbioses with
418 mycorrhizae as well as pathogen defense (reviewed by Martínez-Medina *et al.*, 2019) although
419 these roles are likely not relevant to our root assays in our laboratory using water rather than soil.

420 Oxidative stress is mitigated in part by ferritins, proteins that sequester Fe and thus
421 prevent Fe from reacting with oxygen and producing oxygen radicals. Potri.008G072700
422 encodes a homolog of the four-member ferritin family in *Arabidopsis*, and is most closely related
423 to *FERRITIN 2* (greater Smith-Waterman alignment score) and *FERRITIN 4* (greater residue
424 similarity). The latter homolog has been studied in the context of root system architecture. While

425 increasing concentrations of Fe in media led to an increase in lateral root density, this effect was
426 abolished in triple knockouts of FERRITIN 1, 2 and 4 (Reyt *et al.*, 2015).

427 In addition to catalyzing a PTM of endogenous proteins as previously discussed,
428 glutathione S-transferases (GSTs) such as Potri.001G436800 are well-known to have roles in
429 detoxification of xenobiotics such as herbicides, and have lesser-characterized roles in regulation
430 of redox balance via glutathione, an antioxidant (reviewed by Hernández Estévez & Rodríguez
431 Hernández, 2020). Transgenic studies have found *Arabidopsis* lines overexpressing various GST
432 homologs to have increased tolerance to oxidative stress (Sharma *et al.*, 2014; Xu *et al.*, 2017)
433 and enhanced root proliferation, although more research is needed to determine the specific
434 mechanism or mechanisms by which GSTs regulate root development, whether via ROS, PTMs
435 or other roles (Chen *et al.*, 2012).

436 Other enzymes have more direct roles in oxidative stress and signaling, such as
437 peroxidases that catalyze redox reactions (Yoshida *et al.*, 2003). Potri.004G023100 is an
438 example of a putative peroxidase and is closely related to *Arabidopsis* accessions AT3G01190
439 and AT5G15180, both of which are highly expressed in root apices (Klepikova *et al.*, 2016) but
440 have not been characterized in mutant studies to our knowledge.

441 Agreement with previous GWAS of adventitious rooting in poplar

442 Very few of our gene candidates were also identified as possible regulators of
443 adventitious root traits in published studies. In a prior GWAS in *Populus deltoides x simonii* that
444 employed 434 genotypes and yield 224 QTLs, with multiple possible candidate genes being
445 proposed for a given QTL, an uncharacterized gene believed to be a transcription factor
446 (Potri.005G154200), as well as a putative xyloglucan endotransglucosylase/hydrolase
447 (Potri.016G098600), were associated with rooting traits. They appeared as associations with
448 lateral LRL at week three in our work, and with total number of roots in this prior work (Table
449 S6). Potri.015G026500 encodes an uncharacterized putative phospholipase that is found as
450 associated with lateral LRL at week 3 in our work, and with root volume and total root number
451 in this prior work. Potri.016G098500 encodes a putative heme-binding protein we found to be
452 associated with the first PC of LRL traits (across root types and timepoints) and that Sun *et al.*
453 (2019), found associated with LRL (Table S7). Possible reasons for the relatively low level of
454 overlap between these studies include differences between species of poplar, variation in GWAS

455 populations and statistical methods, as well as the use of different rooting assays (Sun *et al.*,
456 2019).

457 **Conclusion**

458 We performed GWAS to identify regulators of adventitious rooting capacity in 1,148
459 genotypes from a *P. trichocarpa* clone bank. To facilitate the collection of quantitative measures
460 of adventitious root development, we employed a phenotyping system tailored for our
461 adventitious rooting assay in poplar. The hundreds of gene candidates identified include
462 regulators of cell division and structure, hormone signaling, reactive oxygen species signaling
463 and post-translational modifications as well as many genes of miscellaneous or unknown
464 function. The distinct origins of basal and lateral roots were supported both by our multivariate
465 phenotype analysis and GWAS associations. As root development is a complex and polygenic
466 process, future research will benefit from investigation of interactions between genes such as the
467 candidates identified here, functional studies such as through mutagenesis, and differential
468 rooting responses to environmental treatments.

469 **Acknowledgements**

470 We thank the National Science Foundation Plant Genome Research Program for support
471 (IOS #1546900, Analysis of genes affecting plant regeneration and transformation in poplar),
472 and members of GREAT TREES Research Cooperative at OSU for its support of the Strauss
473 laboratory.

474 Support for the Poplar GWAS dataset is provided by the U.S. Department of Energy,
475 Office of Science Biological and Environmental Research (BER) via the Center for Bioenergy
476 Innovation (CBI) under Contract No. DE-PS02-06ER64304. The Poplar GWAS Project used
477 resources of the Oak Ridge Leadership Computing Facility and the Compute and Data
478 Environment for Science at Oak Ridge National Laboratory, which is supported by the Office of
479 Science of the U.S. Department of Energy under Contract No. DE-AC05-00OR22725. We would
480 like to thank the efforts of personnel from the CBI in establishing the GWAS resource used for
481 this study.

482 This work used the COMET high-performance cluster at the San Diego Supercomputing
483 Center (University of California, San Diego) made available through the Extreme Science and

484 Engineering Discovery Environment (XSEDE), which is supported by National Science
485 Foundation grant number ACI-1548562.

486

487 **Author Contributions**

488 Strauss, Li, Jiang, and Muchero designed and directed the overall study, and obtained
489 funding for its execution; Ma, Peremyslova, Magnuson, and Goddard designed and/or executed
490 the phenotypic analyses; Nagle, Yuan, and Damanpreet created, adapted, and executed the
491 machine vision, computation, and data analysis pipelines; Niño de Rivera assisted with
492 inspecting results in IGV. Nagle wrote the manuscript with editing from Strauss, and all others
493 contributed further edits and revisions.

494

495 **Data Availability**

496 Raw data and code used for this project is available upon request to the authors. MTMC-
497 SKAT is available on GitHub (<https://github.com/naglemi/mtmcskat>).

498

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