

# Association mapping identifies loci for canopy coverage in diverse soybean genotypes

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Abstract Rapid establishment of canopy coverage decreases soil evaporation relative to transpiration, improves water use efficiency and light interception, and increases soybean competitiveness against weeds. The objective of this study was to identify genomic loci associated with canopy coverage (CC). Canopy coverage was evaluated using a panel of 373 MG IV soybean genotypes that was grown in five environments. Digital image analysis was used to determine canopy coverage two times (CC1 and CC2) during vegetative development approximately 8 to 16 days apart for each environment. After filtration for quality control, 31,260 SNPs with a minor allele frequency  $(MAF) \geq 5\%$  were used for association mapping with the FarmCPU model. Analysis identified significant SNPcanopy coverage associations including 36 for CC1 and

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M. K. Davies e-mail: mkdavies@uark.edu 56 for CC2. Five SNPs for CC1 and 11 SNPs for CC2 were present in at least two environments. The significant SNP associations likely tagged 33 (CC1) and 50 (CC2) different quantitative trait loci (QTLs). Eleven putative loci were identified in which chromosomal regions associated were coincident for CC1 and CC2. Candidate genes identified using these significant SNPs included those with reported functions associated with growth, developmental, and light responses. Favorable alleles from significant SNPs may be an important resource for pyramiding genes to improve canopy coverage and for identifying parental genotypes for use in breeding programs.

Keywords Soybean . Association mapping . Light interception

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#### Introduction

Genome-wide association analysis is an alternative approach to traditional quantitative trait loci (QTL) mapping of bi-parental populations and is widely used in plant and human genetics (Nordborg and Tavaré [2002](#page-10-0); Risch and Merikangas [1996](#page-11-0)). Genotyping diverse lines provides thousands of single-nucleotide polymorphisms (SNPs) across the genome, which allows fine mapping of complex trait variation down to the nucleotide level by exploiting historical recombination events (Zhu et al. [2008](#page-11-0)). The main advantages of genome-wide association studies (GWAS) over traditional linkage mapping include increased mapping resolution, reduced research time, and greater allele number (Yu et al. [2006](#page-11-0)).

In soybean, GWAS have identified chromosomal regions associated with seed protein and oil concentrations (Hwang et al. [2014](#page-10-0)), carotenoids (Dhanapal et al. [2015a\)](#page-10-0), carbon 13 to 12 ratio (Dhanapal et al. [2015b](#page-10-0); Kaler et al. [2017a\)](#page-10-0), oxygen 18 to 16 ratio (Kaler et al. [2017a\)](#page-10-0), canopy wilting (Kaler et al. [2017b](#page-10-0)), agronomic traits (Wen et al. [2014\)](#page-11-0), and ureide concentration (Ray et al. [2015](#page-11-0)) as well as other studies. GWAS in soybean are likely to increase due to recent genotyping of more than 19,000 accessions of the USDA-ARS Soybean Germplasm collection that provided over 50,000 SNP markers. The complete SNP marker dataset is available at SoyBase [\(www.soybase.org](http://www.soybase.org)).

Early establishment of a closed canopy is beneficial for several reasons. A faster closed canopy increases water use efficiency by enhancing transpiration relative to soil evaporation (Purcell and Specht [2004;](#page-11-0) Rebetzke et al. [2007;](#page-11-0) Richards et al. [2007;](#page-11-0) Slafer et al. [2005\)](#page-11-0). By reducing the water lost through soil evaporation, quick canopy establishment ensures that more soil moisture is available for photosynthesis and biomass production that otherwise would be lost to evaporation.

A second advantage offered by rapid establishment of canopy coverage is improved canopy solar radiation interception, which is an important factor determining crop growth and yield (Edwards and Purcell [2005](#page-10-0); Edwards et al. [2005;](#page-10-0) Liebisch et al. [2015](#page-10-0)). The interception of radiation by the canopy provides the energy required for physiological processes including photosynthesis and transpiration (Liebisch et al. [2015\)](#page-10-0). Capacity of the crop canopy to intercept solar radiation determines yield, which depends on the available leaf area, structure, and its efficiency (Gifford et al. [1984\)](#page-10-0).

Rapid establishment of canopy closure also increases soybean competiveness, especially for weeds (Bussan et al. [1997](#page-10-0)). Herbicide-resistant weeds are becoming a large problem in crop production (Green and Owen [2011\)](#page-10-0), and this problem is mainly due to the high selection pressures imposed by widespread use of mono-herbicide culture (Shaner [1995](#page-11-0)). As the number of herbicide-resistant weeds increase, there is a need for alternative and sustainable approaches to weed management. Faster canopy development can suppress earlyseason weeds (Fickett et al. [2013](#page-10-0); Jannink et al. [2000,](#page-10-0) [2001](#page-10-0)), and rapid canopy development can, therefore, serve as a cultural control method to suppress weed growth by increasing soybean competiveness.

There are differences in competitiveness among soybean genotypes due to how quickly the canopy is established (Place et al. [2011a](#page-10-0), [b](#page-11-0)) that appear to be associated with individual seed weight. Place et al. [\(2011b](#page-11-0)) divided seed lots of three cultivars into five seed weight classes that ranged from 50 to 326 mg seed<sup>-1</sup>. Canopy coverage at 3 weeks after emergence for all genotypes increased with increasing individual seed weight. Larger seed classes improved competitiveness by increasing plant height and petiole length. Small-seeded, natto soybean types were generally slower to establish a canopy compared to large-seeded, tofu type soybean (Place et al. [2011a\)](#page-10-0).

Purcell [\(2000\)](#page-11-0) described a method of analyzing digital images that offers a simple and effective way to determine canopy coverage. Canopy coverage was measured as a fraction of green pixels relative to the total number of pixels in an image, and canopy coverage was approximately equivalent to the fraction of radiation intercepted. Digital-image analysis provides an inexpensive and rapid way of measuring canopy coverage over other methods of estimating radiation interception (Campillo et al. [2008](#page-10-0); Fiorani et al. [2012\)](#page-10-0). The analysis of digital images has been widely accepted as a highthroughput method for determining canopy coverage or the fraction of solar radiation intercepted (De Bruin and Pedersen [2008;](#page-10-0) Edward et al. [2005](#page-10-0); Gaspar and Conley [2015](#page-10-0); Xavier et al. [2017\)](#page-11-0).

Canopy coverage is a quantitative trait that is influenced by genotype, environment, and their interaction (Xavier et al. [2017](#page-11-0)). The complexity of this trait arises from the segregation of alleles at many chromosomal regions, each with small effects on the phenotype, and interacting with other alleles and with the environment (Tuberosa et al. [2007](#page-11-0)). Therefore, investigation of

genetic control of canopy coverage may be used to improve crop performance by selecting and pyramiding favorable loci associated with faster establishment of the canopy into elite cultivars (Xavier et al. [2017](#page-11-0)).

To date, Xavier et al. [\(2017\)](#page-11-0) have conducted the only genetic evaluation of canopy coverage in soybean. They phenotyped the soybean nested association mapping (SoyNAM) population for canopy coverage with a relatively small set of markers (4077 SNPs) and found six genomic regions that were associated with canopy coverage. The SoyNAM panel was developed from crossing 40 genotypes to one hub parent, and from each cross, 140 RILs were developed. Although the SoyNAM panel was selected for diversity, it is likely that these 41 genotypes may be somewhat limited in capturing the wide diversity of phenotypes that would impact canopy coverage. In the present research, 31,260 polymorphic SNPs were utilized for GWAS of canopy coverage, and canopy coverage was assessed on a panel of 373 diverse maturity group (MG) IV accessions. The objective of this study was to use GWAS to explore the genetic variation of canopy coverage present within this panel by identifying significant loci associated with this trait.

## Materials and methods

#### Germplasm collection and field experiments

A panel of 373 MG IV soybean accessions was selected from the USDA-ARS Soybean Germplasm Collection based on genetic diversity and agronomic characteristics ([www.ars.grin.gov](http://www.ars.grin.gov)). Our selection criteria were based on relatively high yield, relatively good lodging and shattering scores, and diverse geographic distribution. A thorough description of genotype selection criteria was provided by Dhanapal et al. ([2015b](#page-10-0)).

Field experiments were conducted in five environments including the Main Arkansas Agricultural Research Center, Fayetteville, AR (FY; 36° 9′N, 94° 17′W), in 2016 on a Captina silt loam; Pine Tree Research Station, Colt, AR (PT; 35° 7′N, 90° 55′W), in 2016 on a Calloway silt loam; Rohwer Research Station, Rohwer, AR (RH; 33° 48′N, 91° 17′W), in 2016 on a Sharkey silty clay; Salina, KS (SA; 38° 70′N, 97° 60′W), in 2016 on a Hord silt loam; and at the Rice Research and Extension Center, Stuttgart, AR (ST; 34° 47′N, 91° 51′W), in 2015 on a Crowley silt loam. Planting dates were 8 June 2015 for ST, 23 May 2016 for RH, 1 June 2016 for FY, 2 June 2016 for PT, and 15 June 2016 for SA. Seeds were planted at a density of 37 m<sup> $-2$ </sup> at a 2.5-cm depth. At ST, plots were 4.57 m long and two rows wide with 0.76-m row spacing. At FY, single row plots were 5.48 m in length with a 0.76 m row spacing. At SA, there were two-row plots that were 3.65 m in length with a 0.76-m row spacing. At PT and RH, seeds were sown with a drill (19-cm row spacing) and plots were 1.52 m wide and 4.57 m long. At each environment, the experiment was conducted as a randomized complete block design with two replications.

For each environment, soil water deficit was estimated for each day beginning at planting as described by Purcell et al. [\(2007](#page-11-0)). Potential evapotranspiration (Eto) for a given day was determined using a modified Penman-Monteith approach (Allen et al. [1998](#page-10-0)) and multiplied by the fraction of radiation intercepted by the crop, which served as a crop coefficient (equivalent to canopy coverage). Estimated soil-water deficits were cumulated and adjusted with rainfall additions as needed.

# Canopy coverage determination

Canopy coverage was determined by analyzing digital images that were taken of the canopy with a camera mounted on a monopod (Purcell [2000\)](#page-11-0). Digital images were taken at 160 cm above the plots at a resolution of  $1280 \times 960$  pixels. For phenotypic variation of canopy coverage at ST, FY, and SA, images consisted of a single row, and at PT and RH, images were taken above the center of the plots and were composed of seven rows. For digital images of single rows, care was taken to ensure that the image was centered directly over the row and that the image frame extended from the center line between the two adjacent rows. At the times these measurements were made, leaves from adjacent rows did not cross the center line between plots. The first set of pictures (CC1) was taken 23 to 28 days after emergence when plants were between V2 and V3. A second set of pictures (CC2) was taken 8 to 16 days later between V4 and V7. Plant densities were measured in a 1-m section of row, and results indicated no significant effect of genotype on the plant density. Weeds potentially interfere with canopy cover estimates, and plots were weed free before taking pictures. Digital images were analyzed using SigmaScan Pro (v.5.0, SPSS, Inc., Chicago, IL) with a macro that utilizes batch analysis (Karcher and Richardson [2005\)](#page-10-0). Software measured the number of green pixels of each image as a fraction of the total pixel count in the frame. SigmaScan Pro has selectable ranges of hue and saturation values for identifying green pixels in images. For each environment, the settings for the hue and saturation were determined for several representative images prior to batch analysis. Typical ranges that selectively identified green leaves without soil background were from 50 to 100 for hue and 0 to 100 for saturation.

Place et al. ([2011b\)](#page-11-0) reported a strong association of early canopy coverage and individual seed weight. Hence, average phenotypic data of individual seed weight (i.e., the average single seed weight based upon 100 seeds) from 3 years (2014, 2015, and 2016) were included in this study to assess a possible association of canopy coverage with individual seed weight at the genomic level.

#### Statistical analysis

Data were tested for heterogeneity of variance by checking the residual plots, which did not show any heterogeneity of variance. Genotype and environment were treated as fixed effects and replication within environment was considered a random effect for analysis of variance (ANOVA). The PROC GLIMMIX procedure  $(\alpha = 0.05)$  of SAS 9.4 (SAS Institute Inc., Cary, NC, USA [2013](#page-11-0)) was used for ANOVA with a model suggested by Bondari [\(2003\)](#page-10-0):

$$
y_{ijk} = \mu + G_i + E_j + (GE)_{ij} + B_{k(ij)} + \varepsilon_{ijk}
$$

where  $\mu$  is the total mean,  $G_i$  is the genotypic effect of the  $i^{th}$  genotype,  $E_j$  is the effect of the  $j^{th}$  environment,  $(GE)_{ij}$  is the interaction effect between the  $i^{th}$  genotype and the  $j<sup>th</sup>$  environment,  $B_{k(ij)}$  is the effect of replications within the  $j^{th}$  environment, and  $\varepsilon_{ijk}$  is a random error following  $N(0, \sigma_e^2)$ . Analysis of variance was independently applied to CC1 and CC2. Descriptive statistics and Pearson correlation analysis for canopy coverage were performed using the PROC UNIVARIATE and PROC CORR procedures  $(\alpha = 0.05)$  of SAS version 9.4, respectively. Broad sense heritability on an entrymean basis was calculated as

$$
H^{2} = \sigma_{G}^{2} / \left(\sigma_{G}^{2} + \left(\frac{\sigma_{GE}^{2}}{k}\right) + \left(\frac{\sigma_{\varepsilon}^{2}}{rk}\right)\right)
$$

where  $\sigma_G^2$  is the genotypic variance,  $\sigma_{GE}^2$  is the genotype by environment variance,  $\sigma_{\varepsilon}^2$  is the residual variance, k is the number of environments, and  $r$  is the number of replications. The PROC VARCOMP of SAS 9.4 with the restricted maximum likelihood estimation (REML) method was used to estimate the above variance components.

For association analysis, the best linear unbiased prediction (BLUP) values were estimated using the PROC GLIMMIX procedure by environment and across all environments (AAE). The BLUP values were used because they reduce the effects of replication (within environment) and the effects of environment (when conducted across multiple environments).

Genotyping and association analysis

Data for a total of 42,509 SNP markers of all 373 genotypes were obtained from the Illumina Infinium SoySNP50K iSelect SNP Beadchip (Song et al. [2013\)](#page-11-0), which are available at SoyBase ([www.soybase.org\)](http://www.soybase.org). Genotype quality controls were applied by eliminating monomorphic markers, markers with minor allele frequency  $(MAF) < 5\%$ , and markers with missing rate higher than 10%. The remaining missing markers in a set of 31,260 SNPs were imputed using a LD-kNNi method, which is based on a k-nearest-neighbor genotype (Money et al. [2015](#page-10-0)) and then used in association analysis. Population structure is a confounding factor in GWAS that induces false associations. Commonly, the mixed linear model (MLM) is used to reduce these false associations. However, these adjustments also compromise true positive associations. As described by Kaler et al. ([2017a,](#page-10-0) [b\)](#page-10-0), the fixed and random model Circulating Probability Unification (FarmCPU) model, developed by Liu et al. ([2016](#page-10-0)), effectively controlled false positives and false negatives using this same genotype panel. Different models (e.g., compressed mixed linear model from GAPIT, GLM and MLM models from TASSEL) were compared based on their Q-Q plots. The FarmCPU model was superior in controlling the false discovery rate compared to other models evaluated. The Q-Q plot of the FarmCPU model resulted in a sharp deviation from the expected  $P$  value distribution in the tail area, indicating that false positives were adequately controlled (data not shown) in agreement with previous research (Kaler et al. [2017b](#page-10-0)). Therefore, FarmCPU was used for association analysis in the present research. Default parameters were used in FarmCPU model as recommended by the developer of FarmCPU (Liu et al. [2016\)](#page-10-0) except in the change of threshold output

<span id="page-4-0"></span>from 0.01 to 1, which allowed all markers to be included in the output Excel file.

Although FarmCPU controlled the false positives and false negatives, we still used a stringent threshold value  $(-\log 10(P) \ge 3.5)$  to declare a significant association between SNPs and canopy coverage. This level of stringency was used to limit the number of associations to those QTLs likely contributing biologically significant effects. This threshold value is more stringent than that reported in other soybean association mapping studies of soybean (Dhanapal et al. [2015a](#page-10-0), [b](#page-10-0); Hao et al. [2012](#page-10-0); Hwang et al. [2014](#page-10-0); Zhang et al. [2015\)](#page-11-0). We also eliminated any SNP from consideration if the allelic effect was less than the standard error of CC1 or CC2 phenotypic measurements. A threshold value of  $P \leq$ 0.05 was used to identify significant SNPs present in more than one environment but only if representative SNPs met a lower association of  $P \le 0.0003$  in at least one other environment.

## Candidate gene identification

Candidate genes were considered when they were with $in \pm 10$  kb of a SNP with a significant association. This distance was chosen because it approximates the average distance between SNPs (18 kb). Candidate genes

Table 1 Descriptive statistics of canopy coverage (fractional) over 373 MG IV plant introductions measured at two time points during vegetative development, CC1 and CC2, for experiments

and their associated functional annotation and biological function were determined using Glyma1.1, Glyma1.0, and NCBI RefSeq gene models in SoyBase ([www.](http://www.soybase.org) [soybase.org\)](http://www.soybase.org) with consideration for those that may have an association with growth, developmental, and light responses.

#### Results

#### Phenotype statistics

There was a broad range of CC1 and CC2 values observed within each environment. Overall all 373 accessions, the range (i.e., maximum value–minimum value) of CC1 values was 0.27 (FY), 0.17 (PT), 0.45 (RH), 0.30 (SA), and 0.23 (ST) (Table 1). For CC2, the range was 0.40 (FY), 0.28 (PT), 0.62 (RH), 0.29 (SA), and 0.50 (ST). Analysis of variance indicated that genotype, environment, and their interaction had significant effects  $(P \le 0.05)$  on CC1 and CC2. Correlations of canopy coverage between environments for CC1 or CC2 were significant and positive  $(0.10 \le r \le 0.39)$  except for the correlation between RH and ST for CC1  $(r = -0.01)$ (Table [2\)](#page-5-0). Correlations between CC1 and CC2 within environments averaged 0.59 and ranged from 0.76 (FY)

conducted at Fayetteville, AR (FY); Pine Tree, AR (PT); Rohwer, AR (RH); Salina, KS (SA); and Stuttgart, AR (ST)

Trait	<b>ENV</b>	Minimum	Maximum	Range	Mean	Heritability $(H^2)$
CC1						
	<b>FY</b>	0.06	0.33	0.27	0.18	0.38
	PT	0.04	0.21	0.17	0.11	0.52
	<b>RH</b>	0.08	0.53	0.45	0.34	0.54
	<b>SA</b>	0.43	0.73	0.30	0.58	0.51
	<b>ST</b>	0.12	0.35	0.23	0.21	0.52
					Overall <sup>a</sup>	0.58
CC <sub>2</sub>						
	FY	0.41	0.81	0.40	0.62	0.46
	PT	0.24	0.52	0.28	0.38	0.21
	<b>RH</b>	0.35	0.97	0.62	0.80	0.46
	SA	0.69	0.98	0.29	0.90	0.33
	<b>ST</b>	0.27	0.77	0.50	0.50	0.49
					Overall	0.51

<sup>a</sup> Broad sense heritability across all environments

	FY CC1	PT CC1	RH CC1	SA CC1	ST CC1	FY CC2	PT_CC2	RH CC2	SA CC <sub>2</sub>	ST CC <sub>2</sub>
PT_CC1	$0.36*$									
RH CC1	$0.25*$	$0.39*$								
SA CC1	$0.26*$	$0.33*$	$0.30*$							
ST CC1	$0.22*$	$0.17*$	$-0.01$	$0.18*$						
FY CC2	$0.76*$	$0.33*$	$0.26*$	$0.28*$	$0.21*$					
PT CC <sub>2</sub>	$0.20*$	$0.30*$	$0.15*$	$0.26*$	$0.18*$	$0.24*$				
RH CC2	$0.26*$	$0.27*$	$0.54*$	$0.31*$	$0.10*$	$0.37*$	$0.39*$			
SA CC <sub>2</sub>	$0.12*$	$0.24*$	$0.21*$	$0.64*$	$0.19*$	$0.13*$	$0.12*$	$0.22*$		
ST_CC <sub>2</sub>	$0.23*$	0.09	0.03	$0.14*$	$0.73*$	$0.26*$	$0.10*$	$0.18*$	$0.13*$	
AVG SW	$0.35*$	$0.28*$	$-0.03$	$0.14*$	$0.41*$	$0.28*$	$0.23*$	$-0.01$	0.05	$0.34*$

<span id="page-5-0"></span>Table 2 Correlation of canopy coverage between environments for first (CC1) and second (CC2) measurement dates, between CC1 and CC2 within each environment, and between canopy coverage and average seed weight (AVG\_SW)

\*Significant correlation at  $P < 0.05$ 

to 0.30 (PT) (Table 2). Broad sense heritability by environment on an entry-mean basis indicated low-tomoderate heritability for CC1 and CC2 (0.21  $\leq H^2 \leq$ 0.54) (Table [1](#page-4-0)). When considered over all environments,  $H<sup>2</sup>$  was 0.58 (CC1) and 0.51 (CC2).

For silt-loam soils in our study (FY, ST, PT, and SA), irrigation is typically recommended when soilmoisture deficits exceed 35 mm, and for the clay soil at RH, irrigation is recommended when soil moisture deficits exceed 50 mm (Purcell et al. [2007](#page-11-0)). Using these irrigation thresholds as indicators of stress, the week prior to CC1, soil moisture was adequate for ST, RH, and SA but was limiting for FY (3 out of 7 days) and PT (7 out of 7 days). Between CC1 and CC2, soil moisture was adequate at ST every day but limiting at FY (3 out of 14 days), PT (5 out of 15 days), SA (9 out of 11 days), and RH (5 out of 9 days). The differences in soilmoisture availability among environments and between CC1 and CC2 likely contributed to the  $G \times E$ effect.

## Genome-wide association analysis

Genome-wide association analysis identified 36 SNPs significantly associated with CC1 at level of  $-\log 10$  (P)  $\geq 3.5$ ; P  $\leq 0.0003$  (Table S1 and Fig. S1) in at least one of the five environments. Of these 36 SNPs, six were significant in at least two environments. Significant SNPs that were present in a linkage disequilibrium block on the same chromosome were considered as one locus. Thus, the 36 significant SNPs comprised 33 putative QTLs (Table S1). There were 56 significant SNPs associated with CC2 at a level of  $-\log 10(P) \geq 3.5$ ; P  $\leq$ 0.0003 (Table S2 and Fig. S2) in at least one environment. Eleven SNPs of these 56 were significant in at least two environments. These 56 significant SNPs comprised 47 putative QTLs (Table S2). The allelic effect (fractional change in canopy coverage for the major compared to the minor allele) for these significant SNPs for CC1 ranged from  $-0.050$  to 0.068 (Table S1) and for CC2 ranged from − 0.048 to 0.086 (Table S2). The positive sign indicates that the minor allele was associated with increased canopy coverage. These allelic effects are in comparison to the standard errors of measurement for CC1 and CC2 of 0.004 and 0.001, respectively. The list of all 33 significant loci for CC1 and 47 significant loci for CC2, their corresponding MAF, major or minor allele, allelic effect,  $R^2$  value, and common environments where SNPs were significant are listed in Tables S1 and S2, respectively. Table [3](#page-6-0) shows the list of significant SNPs associated with CC1 and CC2 that were present in more than one environment, common to both CC1 and CC2, and coincident with previously reported QTLs for canopy coverage (Xavier et al. [2017](#page-11-0)). Association analysis of canopy coverage averaged across all environments identified 11 SNPs and 12 SNPs significantly associated with CC1 and CC2, respectively, at level of − log10 (P)  $\geq$ 3.5; P  $\leq$  0.0003 (Table S5).

Individual seed weight averaged over 3 years for these 373 genotypes was significantly ( $P \le 0.05$ )

<span id="page-6-0"></span>

Table 3 Significant SNPs associated with canopy coverage at the first (CC1) and second (CC2) measurement dates, at both measurement dates (CC1 and CC2), and loci that were coincident with previously reported genomic regions



Table 3 (continued)



Experiments were conducted at Stuttgart in 2015 (ST), Fayetteville in 2016 (FY), Pine Tree in 2016 (PT), Rohwer in 2016 (RH), and Salina in 2016 (SA). Significant SNPs were identified using the FarmCPU model with threshold P value (− log<sub>10</sub> (P) ≥ 3.5; P ≤ 0.0003)

<sup>a</sup> Genomic regions where identified SNPs were coincident with QTLs identified by Xavier et al. ([2017](#page-11-0))

<sup>b</sup> Genomic regions where both CC1 and CC2 were coincident

<sup>c</sup> Allelic effect indicates the difference in mean canopy coverage between genotypes with major allele and minor allele. Positive sign indicates that major allele is associated with increased canopy coverage. Negative sign indicates that minor allele is associated with increased canopy coverage

 $\alpha$ <sup>d</sup> Common ENV indicates that SNP is present in more than one environment

<sup>e</sup> All genes are from the Glyma1.1 assembly [\(www.soybase.org\)](http://www.soybase.org)

correlated with CC1 and CC2 (0.14  $\leq r \leq$  0.41) at 7 of the 10 possible combinations of CC1/CC2 and environment (Table [2\)](#page-5-0). Analysis identified 52 SNPs significantly associated with average individual seed weight at a significance level of  $-\log 10(P) \ge 3.5$ ;  $P \le 0.0003$  (data not shown). Nine chromosomal regions were identified, where QTLs associated with canopy coverage and average seed weight were coincident (six with CC1 (Table S1) and three with CC2 (Table S2)). These associations were important because previous studies showed a positive relationship between individual seed weight and canopy coverage (Place et al. [2011a,](#page-10-0) [b\)](#page-11-0). Identifying the common regions would be useful for further research.

Candidate gene identification

Based on the location of SNPs with significant associations, nearby genes (within  $\pm 10$  kb of the SNP) were identified that may have association with growth, developmental, and light response. There were 36 genes near SNPs tagging CCI and 56 genes near CC2. Of these genes, 19 (CC1) and 21 (CC2) had SNPs with significant associations within the gene. The remaining genes were present within  $\pm$ 10 kb of the respective SNPs. Based on their biological function of growth, developmental, and light response that were reported in SoyBase ([www.](http://www.soybase.org) [soybase.org\)](http://www.soybase.org), 13 genes for CC1 and 19 genes for CC2 are potential candidate genes for establishing faster canopy coverage.

# Discussion

There was wide phenotypic variation of canopy coverage for both CC1 and CC2 within each environment, which is important for dissecting complex traits through association mapping (McCarthy et al. [2008\)](#page-10-0). That there were significant positive correlations between environments for CC1 and CC2, and moderate heritability indicates that canopy coverage can be improved, which has implications for increasing transpiration relative to soil evaporation, light interception, and competitiveness for weeds.

Some of the variability between CC1 and CC2 within environments and among canopy coverage measurements across environments may be related to soilmoisture availability prior to measurements. Drought decreases leaf area development and leaf expansion rate (Clauw et al. [2015](#page-10-0); Manandhar et al. [2017](#page-10-0); Tardieu and Tuberosa [2010](#page-11-0)). The week before CC1 measurements there were no soil-moisture limitations at ST, RH, or SA, but soil-moisture deficits exceeded the threshold for irrigation for 3 or 7 days before CC1 at FY and PT, respectively. Between CC1 and CC2 measurements, ST was the only environment in which daily soil-moisture deficits were above the irrigation threshold.

Of the nine genomic regions common to both average seed weight and canopy coverage, eight had the same directional allelic effect (Tables S1 and S2). For example, a genomic region on Gm01, where both canopy coverage and average seed weight were coincident, there was a positive allelic effect for canopy coverage of 0.02 (Table S1) and this region also had a positive allelic effect for average seed weight of 0.05 g seed<sup>-1</sup>. Both these regions were located within the coding region of a gene, Glyma01g42890, which codes a JUMONJI domain-containing protein with a biological function associated with meristem growth (Table S3). Interestingly, the SNP associated with canopy coverage in this region was present in more than one environment (Table S1). Similarly, two coincident genomic regions on Gm05 and Gm16 also had positive allelic effects for both canopy coverage and average seed weight. These regions were located close to genes, Glyma05g02130 and Glyma16g25880, which have biological functions involved with response to light stimulus (Table S3).

For CC1, 19 major alleles out of 41 were linked with an increase in canopy coverage (positive value of allelic effect indicates that the major allele was associated with an increase in canopy coverage) (Table S1). One SNP on Gm08 that had the largest positive allelic effect (0.07) was present within the coding region of a gene, Glyma08g13160, which codes a chaperone binding protein that has a biological function associated with photosynthesis (Tables S1 and S3). A SNP on Gm16 that had the second largest positive allelic effect (0.05) was also present within the coding region of a gene, Glyma16g25880, which codes a root phototropism protein that has a biological function involved with response to light stimulus (Tables S1 and S3). Out of 41 SNPs, minor alleles of 22 were associated with an increase in canopy coverage (negative value of allelic effect indicates that minor allele was associated with an increase in canopy coverage) (Table S1). One SNP on Gm02 that had a large negative allelic effect  $(-0.03)$ was present within the coding region of a gene, Glyma02g40960, which codes an early growth response protein (Tables S1 and S3).

For CC2, there were 38 out of 56 SNPs for which the major allele associated with an increase in canopy coverage (Table S2). A SNP on Gm18 that had the largest positive allelic effect (0.09) was present within  $\pm$  5 kb range of a gene,  $Glyma18g00530$ , which codes a DNA repair protein (RAD50) that has a biological function involved with meristem structural organization (Tables S2 and S4). Out of 56 SNPs, the minor alleles of 18 were associated with an increase in canopy coverage (Table S2). One SNP on Gm09 with the largest negative allelic effect  $(-0.05)$  was present within  $\pm$ 10 kb range of a gene, Glyma09g30370, which codes a protein functioning as a glutamine synthetase clone R1 that has a biological function involved with leaf senescence (Tables S2 and S4).

Xavier et al. [\(2017](#page-11-0)) identified seven SNPs associated with canopy coverage, but two of the SNPs on Gm10 were close to one another, which they considered as one QTL. They, therefore, reported six QTLs for canopy coverage using the SoyNAM population. Location of the CC1 and CC2 chromosomal regions identified in this study were compared with QTLs reported by Xavier et al. [\(2017\)](#page-11-0) for canopy coverage. Likewise, we compared genomic regions of CC1 and CC2 to see if they were coincident (Table [3](#page-6-0) and Fig. [1\)](#page-9-0). Four out of six QTLs reported by Xavier et al. ([2017](#page-11-0)) were located close to genomic regions that were associated with <span id="page-9-0"></span>CC1 and CC2 in this study (Table [3](#page-6-0) and Fig. 1). Twelve putative loci on Gm02 (2), Gm06, Gm07, Gm09 (3), Gm11, Gm16 (3), and Gm20 were identified, where chromosomal regions were associated with both CC1 and CC2 (Table [3](#page-6-0) and Fig. 1). These chromosomal regions have candidate genes with a direct function associated with response to auxin, response to gibberellic acid, meristem growth, light-regulated protein, early growth response protein, and response to light intensity (Tables S3 and S4). These putative loci may indicate the stability and importance for improving faster canopy coverage and may highlight the important regions of the genome for further investigations.

## Conclusions

A high marker density of 31,260 SNPs with a MAF  $\geq$ 5% was used in this study for association mapping of

Fig. 1 Location of putative loci significantly associated with canopy coverage for both measurement dates, CC1 and CC2, and previously reported six QTLs for canopy coverage

canopy coverage at two dates (CC1 and CC2) in five environments. There were 36 significant SNPs associated with CC1 and 56 significant SNPs associated with CC2 at a significance level of  $-\log 10$  (P) ≥ 3.5. Five significant SNPs for CC1 and 11 SNPs for CC2 were present in at least two environments. The 36 SNPs for CC1 and 56 SNPs for CC2 likely tagged 33 and 50 QTLs, respectively. Four different putative loci were located within four genomic regions that were previously reported (Xavier et al. [2017](#page-11-0)) as QTLs for canopy coverage. Twelve putative loci were identified, where chromosomal regions associated with CC1 and CC2 were coincident. Several of these loci were close to or within genes related to growth and development. We identified significant SNPs that were present in more than one environment, and where chromosomal regions associated with both CC1 and CC2 were found within the same genomic location. This information may be useful in pyramiding alleles for faster canopy coverage



<span id="page-10-0"></span>and for improving radiation interception, WUE, crop growth, and soybean competitiveness.

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