











Characterization of adaptation mechanisms in sorghum using a multireference back-cross nested association mapping design and envirotyping

Vincent Garin ^{1,2,3,†} Chiaka Diallo ^{4,5,†} Mohamed Lamine Tékété ^{6,7,†} Korotimi Théra ^{6,†} Baptiste Guitton,^{2,3} Karim Dagno,⁶ Abdoulaye G. Diallo,⁶ Mamoutou Kouressy,⁶ Willmar Leiser ⁴, Fred Rattunde,⁸ Ibrahima Sissoko,⁴ Aboubacar Touré,⁴ Baloua Nébié ⁹, Moussa Samaké,⁷ Jana Kholová,^{1,10} Angélique Berger,^{2,3} Julien Frouin ^{2,3}, David Pot ^{2,3}, Michel Vaksman ^{2,3}, Eva Weltzien ^{4,8,*}, Niaba Témé,^{6,*} Jean-François Rami ^{2,3,*}

¹Crop Physiology Laboratory, International Crops Research Institute for the Semi-Arid Tropics, Patancheru, 502 324, India

²CIRAD, UMR AGAP Institut, Montpellier, F-34398, France

³UMR AGAP Institut, Univ Montpellier, CIRAD, INRAE, Institut Agro, Montpellier, F-34398, France

⁴Sorghum Program, International Crops Research Institute for the Semi-Arid Tropics, Bamako, BP 320, Mali

⁵Département d'Enseignement et de Recherche des Sciences et Techniques Agricoles, Institut polytechnique rural de formation et de recherche appliquée de Katibougou, Koulikoro, BP 06, Mali

⁶Institut d'Economie Rurale, Bamako, BP 262, Mali

⁷Faculté des Sciences et Techniques, Université des Sciences des Techniques et des Technologies de Bamako, Bamako, BP E 3206, Mali

⁸Agronomy Department, University of Wisconsin, Madison, WI 53705, WI, USA

⁹Dryland Crops Program, International Maize and Wheat Improvement Center (CIMMYT-Senegal) U/C CERAAS, Thiès, Po Box 3320, Senegal

¹⁰Department of Information Technologies, Faculty of Economics and Management, Czech University of Life Sciences, Prague, 165 00, Czech Republic

*Corresponding author: UMR AGAP Institut, CIRAD, University of Montpellier, Avenue d'Agropolis, Montpellier, F-34398, France. Email: jean-francois.rami@cirad.fr;

*Corresponding author: Laboratoire de biotechnologie, Institut d'Economie Rurale, Rue Mohamed V, Bamako, BP 258, Mali. Email: niabateme@gmail.com;

*Corresponding author: Agronomy Department, University of Wisconsin, 371 Moore Hall, 1575 Linden Drive, Madison, WI 53705, USA. Email: eva.weltzien@gmail.com

†C.D., V.G., M.L.T., and K.T. contributed equally to this work.

Identifying the genetic factors impacting the adaptation of crops to environmental conditions is of key interest for conservation and selection purposes. It can be achieved using population genomics, and evolutionary or quantitative genetics. Here we present a sorghum multireference back-cross nested association mapping population composed of 3,901 lines produced by crossing 24 diverse parents to 3 elite parents from West and Central Africa-back-cross nested association mapping. The population was phenotyped in environments characterized by differences in photoperiod, rainfall pattern, temperature levels, and soil fertility. To integrate the multiparental and multi-environmental dimension of our data we proposed a new approach for quantitative trait loci (QTL) detection and parental effect estimation. We extended our model to estimate QTL effect sensitivity to environmental covariates, which facilitated the integration of envirotyping data. Our models allowed spatial projections of the QTL effects in agro-ecologies of interest. We utilized this strategy to analyze the genetic architecture of flowering time and plant height, which represents key adaptation mechanisms in environments like West Africa. Our results allowed a better characterization of well-known genomic regions influencing flowering time concerning their response to photoperiod with *Ma6* and *Ma1* being photoperiod-sensitive and the region of possible candidate gene *Elf3* being photoperiod-insensitive. We also accessed a better understanding of plant height genetic determinism with the combined effects of phenology-dependent (*Ma6*) and independent (*qHT7.1* and *Dw3*) genomic regions. Therefore, we argue that the West and Central Africa-back-cross nested association mapping and the presented analytical approach constitute unique resources to better understand adaptation in sorghum with direct application to develop climate-smart varieties.

Keywords: multiparental populations; quantitative trait loci; multireference BCNAM; genotype by environment interaction; envirotyping; adaptation

Introduction

The genotype by environment (GxE) interaction, which manifests by differential genotypic expressions across environmental conditions (Falconer and Mackay 1996), is an important phenomenon impacting plant development in natural and controlled environments (Campbell and Waser 2001; Annicchiarico 2002). GxE is a fundamental component of plant adaptation (Des Marais et al.

2013), which strongly influences the expression of complex traits (van Eeuwijk et al. 2010). For example, the difference in development response to the length of the day (photoperiod) is a remarkable example of GxE interaction (Nakamichi 2015). An important proportion of genes shows environment-specific behavior, which considerably complicates their use for selection (Bernardo 2016; Cobb et al. 2019). Therefore, the determination of the proportion

Received on 19 October 2023; accepted on 20 December 2023

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of genes influenced by the environment as well as the nature of this influence is a central question. The availability of complex genetic resources, advanced technology to monitor plants in different environmental conditions (envirotyping; Xu 2016), and accurate statistical methods should improve our understanding of the G×E interaction in plants.

Multiparental populations (MPPs) combining the genomes of several founders like the nested association mapping (NAM) design or the multiparent advanced generation inter-cross (MAGIC) design have progressively emerged as central genetic resources for research (Cavanagh et al. 2008; Scott et al. 2020; Bernardo 2021). The NAM design composed of crosses between a recurrent parent and donor parents is a well-spread MPP design (Yu et al. 2008; McMullen et al. 2009; Gage et al. 2020) with examples in maize (Bauer et al. 2013; Chen et al. 2019), rice (Fragoso et al. 2017), wheat (Kidane et al. 2019; Altendorf et al. 2021; Christopher et al. 2021), barley (Maurer et al. 2015; Hemshrot et al. 2019) and sorghum (Bouchet et al. 2017; Marla et al. 2019). Sorghum is also the species that was used to develop the back-cross NAM (BCNAM) design, which consists of introgressing diverse alleles from donors in a recurrent (elite) line using 1 generation of back-cross followed by several generations of selfing (Jordan et al. 2011; Mace et al. 2021).

The BCNAM design has several interesting properties for genetic analyses. Compared to biparental crosses, it addresses a larger genetic diversity and captures more recombination events. Compared to association panels, it offers better control over the population structure, which can reduce false-positive detection (Myles et al. 2009). BCNAM designs also allow the origin of favorable alleles to be traced back to a specific parent, a highly desirable feature in the design of future crosses. MPPs like BCNAM increase rare allele frequencies, which is essential to the precise estimation of their additive effects (Myles et al. 2009). Moreover, an extension of the reference NAM design by the use of several recurrent parents allows the characterization of the genetic effect in multiple genetic backgrounds (Christopher et al. 2021). BCNAM designs are also interesting in the study of G×E because they allow the exposure of structured diversity to contrasting environments, which can maximize the detectable allelic expression (Cobb et al. 2019).

Several approaches have been developed for the detection of single-environment MPP quantitative trait loci (QTL). For example, Li et al. (2011) developed a method based on maximum likelihood QTL effect significance. Xavier et al. (2015) used mixed models employed for genome-wide association analysis. Garin et al. (2017, 2018) proposed a framework assuming different allelic configurations at the QTL position. More recently, Paccapelo et al. (2022) adapted the whole-genome interval mapping method for the NAM design. A more general strategy consists of using models based on probabilistic estimation of identity by descent (IBD) calculated in any type of design (Zheng et al. 2015; Broman 2022). This information can be integrated into models using random QTL effects with the IBD matrix associated (Wei and Xu 2016; Li et al. 2021). A last solution is to estimate MPP QTL effects with a Bayesian approach, which offers an elegant solution to the question of model determination (Wu and Jannink 2004). By treating more sources of randomness in the estimation procedure, can also offer greater precision for haplotype or allelic series effect estimation, but at the price of a higher computational demand (Zhang et al. 2014; Crouse et al. 2020).

Compared to separate within-environment analyses, the QTL detection using MPP data characterized in multiple environments (MPP-ME) in a joint model is more challenging, but it allows a more direct comparison of the estimated effects. Until now, phenotypic values were averaged across environments (e.g. Giraud et al. 2014), which prevents the use of the full potential of those data like the

environmental correlation (Piepho and Pillen 2004). To overcome this limitation, Verbyla et al. (2014) proposed a QTL detection approach for MAGIC populations characterized in ME that allows estimation of environment-specific parental QTL effects. In the same vein, Garin et al. (2020) extended their framework to estimate MPP-ME QTL models with parental or ancestral haplotype effects. Diouf et al. (2020) proposed a forward-backward algorithm for MPP-ME analysis in MAGIC. Finally, De Walsche et al. (2023) proposed approaching MPP-ME QTL detection as a meta-analysis of single environment analyses.

The extension of multi-environment QTL models with environmental covariates (ECs) for biparental populations and MPPs has proven useful in estimating the sensitivity of the QTL effect to specific dimensions of the environment (Malosetti et al. 2004; Boer et al. 2007; Garin et al. 2020). Recent advances in sensor technology have considerably increased the availability of high-resolution environmental characterization and the possibility of integrating this information into genetic analysis, often termed envirotyping (Xu 2016; Costa-Neto et al. 2021). In this study, we propose an approach to integrate the available high-resolution environmental information in MPP-ME QTL models to improve our understanding of the QTL×E interaction by testing the sensitivity of multiple alleles to various ECs.

Photoperiod is a key EC for sorghum development, especially in West Africa. Photoperiodism is the developmental response of plants to the relative length of daylight or photoperiod (Hopkins 2008). The influence of photoperiod on flowering time is particularly important for sorghum because it represents an important source of adaptation by adjusting the length of the vegetative and reproductive phases given local environmental conditions (Kouressy et al. 2008). Sorghum is a short-day plant generally sensitive to photoperiod that delays its panicle initiation when days become longer (Wolabu and Tadege 2016). The flowering time can be represented as a broken linear function of the photoperiod with a baseline duration remaining constant until a certain photoperiod and then an increasing slope where flowering time increases with the photoperiod (Van Oosterom et al. 2001; Fig. 4g). Photoperiod sensitivity is the variation in the steepness of the slope. Next to photoperiod, temperature is another environmental covariate that is assumed to influence sorghum flowering time at the genetic level (Mace et al. 2013).

In this article, we present a multireference sorghum BCNAM of populations composed of 24 diverse parents anchored on 3 West African elite lines that represents one of the most relevant publicly available resources for West and Central Africa sorghum (WCA-BCNAM, Table 1, Supplementary Fig. 1). The population was phenotyped for 8 traits covering phenology and yield component aspects of the plant in ME. To analyze those data, we developed MPP-ME QTL models integrating environmental covariables. We illustrate our approach through a fine characterization of major QTL for flowering time and plant height.

Material and methods

Figure 1 is an overview of the proposed analytical strategy. In the following sections, we will first describe the data used. Then, we will present the statistical models for phenotypic analyses, MPP QTL×E analysis extended with ECs, and the procedure to project QTL behavior beyond the tested environments.

Plant material

The WCA-BCNAM is composed of 3 BCNAM populations produced after the crossing of the Grinkan (GR), Kenin-Keni (KK), and Lata3

Table 1. WCA-BCNAM parents with racial classification, origin, relative height (PH), relative maturity, reaction to photoperiod sensitivity (Kp3), and specific advantages. The last 3 columns specify the crossing scheme with the year when the cross was phenotyped (2012 and/or 2013).

Parent information								Crossing scheme		
Parent	Race	Origin	PH	Mat	Kp3	Specific advantage	References	GR	KK	LT
GR	G/C	Mali	av	av	av	Elite line	Guillon <i>et al.</i> (2018)			13
KK	G/C	Mali	av	av	av	Elite Line	Leroy <i>et al.</i> (2014)			
LT	G/C	Mali	+	av	av	Elite Line	Diallo <i>et al.</i> (2019)			
Fara-Fara	G	Nigeria	+	+	+	Diversity	Andrews (1973)	12	12	13
E36-1	C	Ethiopia	-	av	-	Drought tolerance	Mahalakshmi and Bidinger (2002)	12/13	12	
IS15401	G	Cameroon	+	+	+	Striga resistance	FAO (2008)	12	12	13
IS23540	C	Ethiopia	-	av	-	Sweet stem	FAO (2023)	12	13	13
B35	D/C	Ethiopia	-	-	-	Drought tolerance	Rama Reddy <i>et al.</i> (2014)	12	12	
Konotene	D	Mali	+	+	+	Grain weight	Clément <i>et al.</i> (1980)	12		
SC566-14	C	Nigeria	-	-	-	Al tolerance	Magalhaes <i>et al.</i> (2004)	12		13
Framida	C	S. Africa	-	+	-	Striga resistance	Hausmann <i>et al.</i> (2001)	12		13
CSM417	G	Mali	+	+	+	Grain quality	Clément <i>et al.</i> (1980)	12	12/13	
CSM63	G	Mali	av	-	-	Precocity	Chantereau <i>et al.</i> (1998)	12		
CSM388	G	Mali	+	+	+	Grain quality	Folliard <i>et al.</i> (2004)	12/13		
Gadiaba Dié	D	Mali	+	+	+	Grain weight	Clément <i>et al.</i> (1980)	12		
W. Kaura	D/C	Nigeria	-	+	+	Diversity	Goma <i>et al.</i> (2012)	12		
V33/08	G/C	Mali	av	+	av	Grain quality	Soumaré <i>et al.</i> (2008)	13		
Kalaban	C	Mali	-	av	-	Productivity	FAO (2008)	13	13	
Malisor 84-7	C	Mali	-	-	+	Head bug resistance	Ratnadass <i>et al.</i> (2002)	13	13	
BimbG	G	Guinea	+	+	+	Grain quality	Sagnard <i>et al.</i> (2011)	13	13	
Hafijeka	G	Gambia	+	+	+	Grain quality	Folkertsma <i>et al.</i> (2005)	13		13
S. Kaura	D/C	Nigeria	+	+	+	Diversity	Kassam and Andrews (1975)	13		13
Sangatigui	G	Mali	av	av	av	Diversity	CEDEAO-UEMOA-CILSS (2016)		13	
DouaG	G	Mali	+	+	+	Low-P adaptation	Kante <i>et al.</i> (2017)			13
Gnossiconi	G	Burkina F.	av	av	av	Yield stability	vom Brocke <i>et al.</i> (2014)			13
Ngolofing	G	Mali	+	av	+	Grain quality	Clément <i>et al.</i> (1980)			13
Sambalma	G/C	Nigeria	+	+	+	Al tolerance	Kante <i>et al.</i> (2019)			13

Race: D: durra; C: caudatum; G: guinea. Photoperiod sensitivity (Kp3): -Kp < 0.4; av 0.4 < Kp < 0.6; + 0.7 < Kp < 1. PH: -PH < 1 m; av 1m < PH < 2 m; + PH > 2 m. Maturity (cycle): -cycle < 70 days; av 70 days < cycle < 110 days; + cycle > 110 days (These estimations were carried out under early sowing conditions (June) in Mali; Thera 2017).

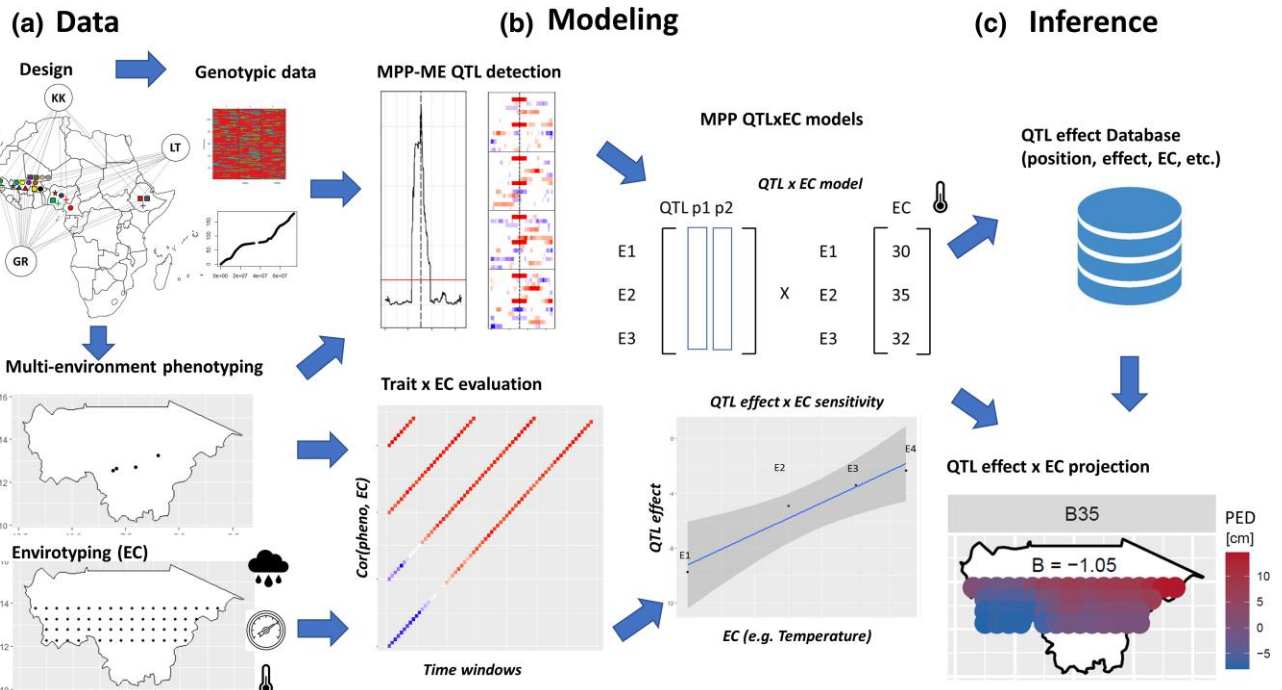


Fig. 1. Overview of the analytical strategy. a) Raw genotypic, phenotypic and environmental covariables; b) Statistical models for QTL detection in MPP characterized in ME, correlations between trait and EC analysis, and synthesis in QTLxEC models; c) Inference using the results gathered in a database and projection of the QTL effect beyond the tested environments.

(LT) recurrent parents with 24 donor parents representative of the Western African sorghum diversity with lines from Central and Eastern Africa (Table 1, Supplementary Table 1: parents name synonyms). The whole population contains 3,901 BC₁F₄ genotypes from 41 crosses (GR: 2,109 genotypes, 19 crosses; KK: 896 genotypes 10 crosses; LT: 896 genotypes, 12 crosses, Supplementary Fig. 1). The LT population crosses involved male sterile sister lines of LT to produce the BC₁ generation, while the BC₁ generations of GR and KK crosses were produced using manual emasculatation. The recurrent parents are elite lines selected in Mali through farmer variety testing. GR was developed through pedigree breeding methods. KK was derived from a directed recurrent selection population involving local parents of different botanical types (Leroy et al. 2014). LT was selected from a random mating population of Guinea parents (Diallo et al. 2019). During the development of the populations, moderate selection pressure was applied at the BC₁F₂ generation against too early flowering and too high genotypes.

The recurrent parents were chosen for their productivity, their adaptation to soil and climate, and their resistance to major biotic and abiotic stresses. The recurrent lines also have weaknesses like poor grain quality and mold susceptibility (GR), suboptimal glume opening and/or susceptibility to *Striga hermonthica* (LT), and low productivity and yield stability (KK). The 24 donor parents cover diverse racial (Guinea, Caudatum, Durra) and geographical origins (Table 1). They are characterized by key adaptive traits like height, maturity, and photoperiod sensitivity (Kp3). Those parents were also selected for traits like tolerance to *Striga hermonthica*, soil phosphorus deficiency and/or drought, and good grain quality that could increase farmer acceptance. Several donor parents were tested with multiple genetic backgrounds. Fara-Fara, IS15401, and IS23540 were crossed with the 3 recurrent parents. Ten donor parents were tested in 2 genetic backgrounds.

Genotypic data

The 3,901 offspring and their parents were genotyped using genotype by sequencing (GBS, Elshire et al. 2011) with 384-plex libraries on an Illumina HiSeq 2000 sequencer. The offspring were genotyped at generation BC₁F₃. The sequence data were analyzed running the reference genome-based TASSEL GBS pipeline (Glaubitz et al. 2014). Unique tags (3,844,911) were aligned on the sorghum reference genome v2.1 (Paterson et al. 2009). After the filtering of raw genotype data for minor allele frequencies (MAF < 0.05) and single marker missing data (< 0.9), 51,545 segregating single nucleotide polymorphisms (SNPs) were identified between the parents with between 11,856 and 26,128 SNPs segregating in the individual crosses. Missing values in the parents were imputed using Beagle (Browning et al. 2018). Missing values in the offspring genotypes were imputed using FSFHap (Bradbury et al. 2007). We determined a unique genetic consensus map (Supplementary Table 2) by projecting the physical distance of the 51,545 markers on a high-quality genetic consensus map (Guindo et al. 2019) using the R package ziplinR (<https://github.com/jframi/ziplinR>).

Phenotypic data

Because of logistic constraints, the GR and KK populations could not be entirely phenotyped during 1 season. Therefore, the crosses of those populations were phenotyped over 2 seasons (2012 and 2013, Table 1, Supplementary Fig. 1). Due to minimal overlap between the genotypes phenotyped in 2012 and 2013 (maximum of 2 crosses per recurrent parent), GR (GR2012, GR2013) and KK (KK2012, KK2013) subpopulations were analyzed independently. Each subpopulation was phenotyped in a combination of

2 locations (Sotuba and Cinzana, Fig. 5a) for 2 sowing dates (Sowing 1: end of June, sowing 2: 3–4 weeks later, Supplementary Table 3), totaling 4 environments (SB1, SB2, CZ1, CZ2; Supplementary Fig. 2). The Sotuba location is characterized by around 900 mm/year of precipitation and lower temperatures, while the Cinzana location is characterized by lower precipitation (600–700 mm/year) and higher temperatures. In both locations, the second sowing date had a lower level of precipitation and humidity and higher temperatures (Supplementary Fig. 2, Supplementary Table 4). In each environment, the progenies of the GR and KK populations were laid out as an augmented design (Kempton 1984), with the 3 recurrent parents used as checks. The LT population was entirely phenotyped in 2013 in 3 environments defined by 2 levels of phosphorus fertilization (low-P and HIGH-P) at the Samanko station and standard conditions at the Kolombada station (Fig. 5a). In each environment, the genotypes were laid out as an alpha-lattice design (Kempton 1984) with 2 replications (Diallo et al. 2019).

We measured 8 traits listed hereafter with crop ontology (CO) code. Flag leaf appearance (FLAG, CO_324:0000631) was the number of days after sowing when half of the plot had their ligulated flag leaves visible. For the QTL analysis, FLAG data were converted into degree day (DD). Plant height (PH, CO_324:0000623) was the distance in cm between the soil and the panicle top. The number of internodes (NODE_N, CO_324:0000605) was the number of nodes on the main stem –1 and the average length of the internodes (NODE_L) was the main stem length divided by NODE_N. The peduncle length (PED, CO_324:0000622) was the distance in cm between the final node and the panicle bottom. The panicle length (PAN, CO_324:0000620) was the distance in cm from the end of the peduncle to the panicle top. Grain weight (GWGH) (CO_324:0000424) was the weight in grams of 1000 grains. Finally, YIELD (CO_324:0000403) was measured in kg/ha at the plot level. All traits except FLAG were measured at harvest. Some traits, like GWGH and PAN, were not measured in all environments (Supplementary Table 5).

Environmental covariables—ECs

We complemented the data by 15 daily observed ECs (Supplementary Table 6) to evaluate the environmental influence on plant adaptation of the GR and KK populations. With 4 environments (SB1, SB2, CZ1, CZ2) we could observe environmental gradients, which was not possible for the LT data. The ECs were divided into 3 categories. The atmospheric ECs contained: cumulated rain (mm), humidity (%), vapor pressure deficit (VPD—kPa), slope of saturation VP curve (SVP—kPa/d), potential evapotranspiration (ETP—mm/day), and atmospheric water deficit (PETP—mm/day). The temperature ECs covered: maximum and minimum temperatures (d), temperature range (d), the effect of temperature on radiation use efficiency (FRUE; 0–1), and cumulated DD. The radiation ECs were the cumulated hours of sun (hSun), the photoperiod (day length) (h), and the solar radiation (MJ/m²/day). We also included the photothermal time as the product between photoperiod and DD. A principal component analysis of the environments' EC values showed important differences between the environmental conditions and a good coverage of the EC variability (Supplementary Fig. 3).

The EC values came from weather stations at the field experiments complemented by Nasapower satellite observations (Spark 2018) and transformation using the R package EnvRtype (Costa-Neto et al. 2021). We projected the genetic effects beyond the tested environments, using compiled environmental data from various sources extended with EnvRtype for a grid of

60 points between 12.25 and 13.75 degrees of latitude and -12.5 and -2 of longitude (Fig. 5).

Phenotypic data analysis

We estimated the genotypic variance component and broad-sense heritability (h^2) using the following mixed model:

$$\underline{y_{icjkl}} = E_j + R(E)_{jk} + \underline{B(R, E)_{jkl}} + C_c + \underline{G(C)_{ic}} + \underline{GE(C)_{ijc}} + \underline{e_{icjklm}} \quad (1)$$

Where, y_{icjkl} = plot phenotypic observation of the i th genotype from cross c in environment j , replication k , and block l ; E_j = environment effect; $R(E)_{jk}$ = replication effect within-environment (only for LT subpopulation); $B(R, E)_{jkl}$ = block effect within replication and environment; C_c = cross effect; $G(C)_{ic}$ = genotype effect conditional on cross; $GE(C)_{ijc}$ = GxE effect conditional on cross. The underlined terms were considered as random, and the other ones as fixed. The genotype, GxE, and error terms were normally distributed with cross-specific variance ($\sigma_{G(cr)}^2$, $\sigma_{GE(cr)}^2$, $\sigma_{e(cr)}^2$). We estimated the model components using Genstat 18 (VSN International 2022). Given those, we calculated the broad-sense h^2 using the formula of Hung et al. (2012):

$$h^2 = \frac{\sigma_{G(cr)}^2}{\sigma_{G(cr)}^2 + \frac{\sigma_{GE(cr)}^2}{N_{env}} + \frac{\sigma_{e(cr)}^2}{(N_{env} * N_{rep})}}$$

Where, N_{env} is the number of environments and N_{rep} the number of replications. For the multi-environment QTL analysis, we calculated within-environment best linear unbiased estimates (BLUEs) by removing the environment and cross term from model 1 and by considering the genotype term as fixed. We used the plot field coordinates to model the spatial variation using a 2D P-spline (SpATS model, Rodriguez-Alvarez et al. 2018). We performed correlation analyses of the BLUEs to investigate the relationships between traits.

Environmental covariable selection

For each subpopulation (GR2012, GR2013, KK2012, KK2013) by trait combination, we selected the 5 ECs that had the strongest influence on the phenotype and the time window where this effect was maximal using the method of Li et al. (2018). This method consists of calculating the correlation between the trait BLUE means across the environments and the EC values inside time windows of different sizes (20, 40, 60, 80, or 100) starting on different days of the plant cycle. We selected the 5 ECs with the highest overall average correlations and determined the most influential window and corresponding EC values as the one with the highest EC-trait correlation. Those EC values and time windows were later used in the QTLxEC models.

MPP QTLxEC modeling

To detect QTL and characterize their effect, we performed a sequential analysis with models increasing in complexity. We started by detecting QTL positions with an extended version of the linear mixed model 3 proposed by Garin et al. (2020):

$$\underline{y_{icj}} = E_j + C_{cj} + x_{ip} * \beta_{pj} + \underline{GE_{icj}} + \underline{e_{icj}} \quad (2)$$

Where, y_{icj} = BLUE of genotype i from cross c in environment j . E_j = environment effect and C_{cj} = within-environment cross

effect. We assumed that the QTL effect was multi-allelic with a different allelic effect carried by each parent. Indeed, the potential existence of multiple alleles (Graud et al. 2014), of multiple genomic regions controlling the trait with cross-specific differences of frequency including absence of segregation and fixation (Xu 1998; Holland 2007), as well as of difference of linkage disequilibrium in different crosses (Bauer et al. 2013) make the multi-allelic hypothesis realistic. The use of a parental model is a common procedure in MPP QTL detection (Li et al. 2011; Bardol et al. 2013; Garin et al. 2017), which presents the advantage of linking the source of the QTL effect to an identified parent (Christopher et al. 2021). Therefore, the QTL position, x_{ip} represented the number of alleles from parent p carried by genotype i . It was inferred by looking at marker score similarity between the genotype and its parent within cross. An alternative bi-allelic model would infer genetic similarity by looking only at marker score similarity ignoring the cross information. Accordingly, β_{pj} represents the QTL allelic effect of parent p in environment j . The recurrent parent was set as a reference. The overall QTL effect significance was estimated using the Wald test (Verbeke et al. 1997), which is a standard procedure to test for fixed effects significance in mixed models. Under H_0 , all parent environment-specific effects (β_{pj}) were assumed to be equal to 0, and the test statistic followed a chi-squared distribution with N alleles degrees of freedom. Under H_1 , at least one $\beta_{pj} \neq 0$.

The GE_{icj} term is the residual genetic by environment variation and e_{icj} is the plot error term that cannot be estimated separately due to the nonreplicated nature of the BLUEs. To model the ($GE_{icj} + e_{icj}$) term, we extended the model from Garin et al. (2020) using an unstructured variance covariance (VCOV) structure (Boer et al. 2007). The unstructured model estimates 1 (co)variance ($\sigma_{G_i, j}^2$) for each pair of environments, which requires an estimate of $N_{env} * (N_{env} + 1) / 2$ parameters. For example, for 2 genotypes (i and i') measured in 4 environments the VCOV is equal to

$$V = \begin{bmatrix} y_{i,1} \\ y_{i',1} \\ y_{i,2} \\ y_{i',2} \\ y_{i,3} \\ y_{i',3} \\ y_{i,4} \\ y_{i',4} \end{bmatrix} = \begin{bmatrix} \sigma_{G_1}^2 & 0 & \sigma_{G_{1,2}}^2 & 0 & \sigma_{G_{1,3}}^2 & 0 & \sigma_{G_{1,4}}^2 & 0 \\ & \sigma_{G_1}^2 & 0 & \sigma_{G_{1,2}}^2 & 0 & \sigma_{G_{1,3}}^2 & 0 & \sigma_{G_{1,4}}^2 \\ & & \sigma_{G_2}^2 & 0 & \sigma_{G_{2,3}}^2 & 0 & \sigma_{G_{2,4}}^2 & 0 \\ & & & \sigma_{G_2}^2 & 0 & \sigma_{G_{2,3}}^2 & 0 & \sigma_{G_{2,4}}^2 \\ & & & & \sigma_{G_3}^2 & 0 & \sigma_{G_{3,4}}^2 & 0 \\ & & & & & \sigma_{G_3}^2 & 0 & \sigma_{G_{3,4}}^2 \\ & & & & & & \sigma_{G_4}^2 & 0 \\ & & & & & & & \sigma_{G_4}^2 \end{bmatrix}$$

We detected QTL by performing a simple interval mapping to select cofactors followed by a composite interval mapping. To reduce the computational demand of the QTL detection scans, we calculated an approximate test statistic similar to the generalized least square strategy implemented by Kruijer et al. (2015; Method S1). The cofactors and final QTL were selected per chromosome using an iterative process: (1) select the most significant position; (2) exclude the position inside the window; (3) repeat until no free position is significant. The cofactor and QTL detection threshold was set at $1 - (1 - 0.05)^{\frac{1}{M_{eff}}}$, where M_{eff} was the effective number of markers accounting for multiple testing determined with the procedure of Li and Ji (2005) (Supplementary Table 7: threshold values). We selected a maximum of 1 cofactor per chromosome to avoid model overfitting. The QTL exclusion window was set to 20 cM. We estimated a global R squared for the whole set of QTL as well as partial R squared for each final selected QTL position using a linear model.

After detecting QTL, we determined if the parental allelic effects composing the overall QTL effect had significant QTL by environment interactions (QEI). For that purpose, we decomposed the parental QTL effects into a main effect component (α_p) and a QEI component (β_{pj}) that were estimated simultaneously, which give the following multi-QTL model

$$y_{icj} = E_j + C_{cj} + \sum_{q=1}^{n_{QTL}} x_{iqp} * (\alpha_p + \beta_{pj}) + \underline{GE}_{icj} + e_{icj} \quad (3)$$

We tested for the significance of the α_p and β_{pj} terms using the Wald test (P -value < 0.05). Those tests allowed us to determine if the parental effects were significant (α_p or β_{pj} significant), and if the parental alleles interacted with the environment (β_{pj} significant). For the parents with a significant QEI (pxE), we replaced the β_{pj} with $EC_j * S_p + l_{pe}$ to test the environmental sensitivity of the QTL allele with respect to the environmental covariate EC_j (e.g. humidity) that represent the EC value in environment j associated with the sensitivity term S_p and the residual effect l_{pe} . The fitted model was the following:

$$y_{icj} = E_j + C_{cj} + \sum_{q=1}^{n_{QTL}} x_{iqp} * (\alpha_p + \beta_{pj}) + x_{iqpxE} (\alpha_p + EC_j * S_p + l_{pe}) + \underline{GE}_{icj} + e_{icj} \quad (4)$$

We estimated model 4 for the 5 most influential ECs previously determined the significance of the sensitivity term S_p using again the Wald test (P -value < 0.05). For the parental alleles showing at least 1 significant EC interaction, we could predict the allelic effect beyond the tested environments by substituting the average EC_e values over the next seasons (2014–2020) for a grid of 60 points in the QTL sensitivity equation ($Q_{eff} = \hat{\alpha}_p + EC_j * \hat{S}_p$). The estimation of model 3 and 4 effects was done using an exact restricted maximum likelihood. The methodology was added to the mppR R package (Garin et al. 2018).

We considered that QTL positions detected for the same trait but in different subpopulations (e.g. GR2012 and LT) represented the same “unique” QTL position if they were distant by less than 10 cM. For each trait, we iteratively identified unique QTL positions by searching for groups of QTL with a maximum distance of 10 cM between the 2 most extreme positions, starting with the positions with the smallest distance. We searched for candidate genes behind the unique QTL positions using the sorghum QTL atlas (Mace et al. 2019).

Results

Genetic diversity

Figure 2a illustrates the genetic diversity covered by the parental lines of the WCA-BCNAM population compared to a panel representative of the global sorghum diversity (Supplementary Method 2) and the parent of the sorghum US-NAM (Bouchet et al. 2017). Overall, the WCA-BCNAM parents covered from 69.9 to 86.8% (depending on the MAF threshold applied to the SNP dataset) of the global sorghum genetic diversity, which offers a better coverage than the parents from the sorghum US-NAM which captured 38.12–57.5% of the considered diversity (Supplementary Method 3 and Table 8). Principal component analysis of the WCA-BCNAM genetic data (Fig. 2b–d) detected 3 distinct groups corresponding to the 3 recurrent parents

(Supplementary Fig. 4). Clear subdivisions of the populations according to the donor parent race and some specific divergences from this general pattern (e.g. Hafjeka Guinea margaritiferrum accession) were observed.

Phenotypic data

The differences between the adjusted phenotypic value distributions were substantial, with medium to large standard deviations [e.g. 130 degree days (~ 7 days) for FLAG, 43 cm for PH, or 892 kg/ha for YIELD]. The phenotypic value distributions were also characterized by large ranges, with 47 days for FLAG and 289 cm for PH (Supplementary Fig. 5). The average heritability values over populations were larger for FLAG (0.78–0.95), NODE_L (0.8–0.9), PH (0.76–0.88), and PED_L (0.68–0.9) compared to PAN_L (0.38–0.77), NODE_N (0.4–0.66), GWGH (0.09–0.89), or YIELD (0.37–0.64) (Supplementary Table 9). Heritability values were larger in the LT subpopulation, which is due to the within-environment replication as well as the greater similarity between the environmental conditions in which the LT subpopulation was phenotyped.

In terms of correlations between the BLUEs of traits (Supplementary Figs. 6 and 7), we observed an overall negative relationship between FLAG and YIELD with an average Pearson correlation of -0.28 (P -val = 0.01) and a standard deviation of 0.17 over the different subpopulations and environments. This negative relationship was observed in all genetic backgrounds. FLAG and NODE_N were positively correlated in all genetic backgrounds. Concerning the correlation of PH with its components, the strongest 1 was with NODE_L (0.74 ± 0.12 ; P -val < 0.001), and the weakest with NODE_N (0.26 ± 0.14 ; P -val = 0.06). It took intermediary values for PED (0.53 ± 0.15 ; P -val = 0.06) and PAN (0.41 ± 0.13 ; P -val = 0.06). This pattern was observed in all configurations. PH was positively correlated with YIELD (0.23–0.56 P -val = 0–0.007), except for the GR subpopulation measured in 2013 at Sotuba (-0.11 ± 0.01 P -val = 0.13). Finally, GWGH was generally correlated with YIELD (0.27 ± 0.18 P -val = 0.03), with a stronger correlation in KK 2012 (0.46 ± 0.01 P -val < 0.001). The ECs influencing the traits the most and the time windows when the influence was maximal are listed in Supplementary Table 10 and Fig. 8.

QTL detection—general results

The total length of the consensus genetic map was 1412 cM, with a number of cross-overs equal to 47,669, 20,343, and 20,120 in the GR, KK, and LT populations, respectively (Supplementary Table 2). We detected 100 significant QTL over the 5 subpopulations and 8 traits, which represented 64 unique QTL (Table 2, Supplementary Fig. 9). The total variance explained by the QTL was rather large for FLAG (32–53%), PH (10–48%), and NODE_L (11–47%), moderate for PED (10–32%), NODE_N (10–22%), and GWGH (8–30%), and low for YIELD (4–14%) and PAN (5–9%).

QTLxEC extend

Each of the 100 significant QTL was modeled by assuming $N_{par(sub-pop)} - 1$ allelic effects, which represented a total of 948 effects for which we could estimate the significance of the main and GxE additive effects (Supplementary Table 11). Overall, 51% of the parental alleles presented significant effects, 26% interacted with the environment (238 alleles corresponding to 87 QTL), and 16% interacted with at least 1 EC (128 alleles corresponding to 61 QTL). The FLAG, PH, and PED QTL were more significantly affected by the EC than the QTL of PAN and YIELD (Supplementary Table 12). For example, photoperiod strongly

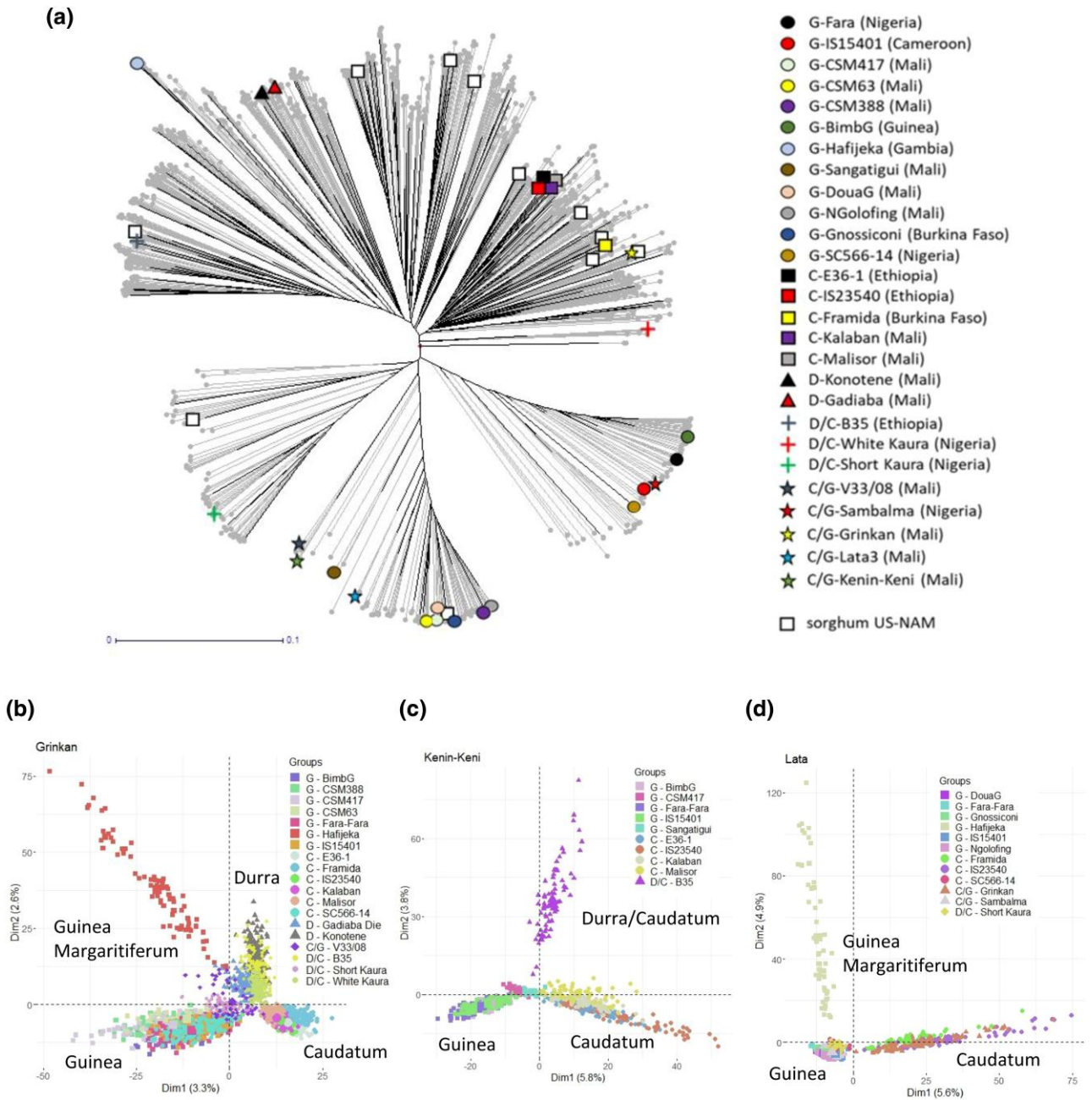


Fig. 2. Genetic diversity and structure of the WCA-BCNAM design. a) Coverages of the global sorghum molecular diversity by the WCA-BCNAM and sorghum US-NAM (white square, Bouchet et al. 2017) parents. Principal component biplots performed on a subset of 5,000 markers randomly selected from the b) GR c) KK d) LT subpopulations.

influenced FLAG, NODE_N, and PH QTL. Atmospheric ECs like VPD influenced PED and NODE_L QTL effects, while YIELD QTL was sensitive to humidity. PAN and NODE_L QTL were sensitive to minimum temperature.

QTL with large effects and candidate genes

Eleven QTL showed medium to large effects ($R^2 \in [2.7 - 29.9]$) with strong significance and consistency over several subpopulations and environments (Table 3 and Supplementary Fig. 9). The range of the parental allelic effects could reach 300 dd (around 15 days) for FLAG, or 1.07 m for PH, which accounts for an important fraction of the phenotypic variability (Supplementary Fig. 5). On chromosome 3, we detected a strong QTL for FLAG

(QTL_FL_3_78) which was significant in all subpopulations and environments. Almost at the same position, we also detected a large effect QTL for NODE_N (QTL_NN_3_78). QTL_FL_3_78 and QTL_NN_3_78 are probably linked to the early flowering (*Elf3*) possible candidate gene (Guitton et al. 2018) or *SbCN12* (Yang et al. 2014). Another FLAG QTL (QTL_FL_6_3) with a consistent effect in all subpopulations and environments was detected at the beginning of chromosome 6. It colocalized with a QTL for NODE_N (QTL_NN_6_2). Those QTL could be related to the *Ma6* gene (Rooney and Aydin 1999; Murphy et al. 2014). We also detected a QTL with medium effects on FLAG on chromosome 6 around 36 cM (QTL_FL_6_38) in the region of the *Ma1* gene (Murphy et al. 2011) and another on chromosome 9 around 105 cM

Table 2. Number of QTL detected for the traits and reference genotype by year combinations. Total R^2 explained by the QTL are provided in parentheses.

	FLAG	PH	NODE_N	NODE_L	PED	PAN	GWGH	YIELD
Grinkan 2012	6 (48.9)	3 (48)	4 (17.6)	2 (47.1)	6 (31.2)	5 (8.5)	3 (13.5)	3 (5.4)
GR 2013	4 (32.1)	4 (44.5)	1 (9.6)	2 (42.6)	2 (21.1)	1 (4.6)	0	2 (7.3)
KK 2012	6 (53.4)	2 (9.6)	2 (16.8)	3 (18.8)	3 (14.3)	2 (5.2)	2 (7.9)	1 (3.9)
KK 2013	2 (35.5)	2 (12.7)	2 (22.3)	0	2 (16.9)	1 (5.8)	0	1 (5.9)
LT	4 (50.3)	2 (20.1)	2 (13.7)	1 (11)	2 (10.2)	0	6 (30.4)	4 (14.3)

Table 3. List of large and medium effect QTL with trait, chromosome, position, average R^2 , QTLx E effect range, number of parental alleles with significant effects, and candidate genes.

QTL ID	Trait	chr	Range (cM)	Range (Mbp)	R^2	Qx E range	Npar	Candidate genes
Q_FL_3_78	FLAG	3	77.34–78.36	51.1–51.5	17.1	(–123; 144) (dd)	21	<i>Elf3</i> , <i>SbCN12</i>
Q_NN_3_78	NODE_N	3	78.13–78.75	51.4–51.7	9.3	(–1.8; 2.1) (n)	15	<i>Elf3</i> , <i>SbCN12</i>
Q_FL_6_3	FLAG	6	1.49–2.94	0.4–0.8	19.4	(–178; 130) (dd)	17	<i>Ma6</i>
Q_NN_6_2	NODE_N	6	1.49–2.73	0.4–0.8	7.9	(–2.6; 1.8) (n)	15	<i>Ma6</i>
Q_FL_6_38	FLAG	6	36.32–39.4	40.4–41.2	6.3	(–192; –27) (dd)	6	<i>Ma1</i>
Q_FL_9_105	FLAG	9	103.7–106.7	54.6–55.4	2.7	(–40; 91) (dd)	9	<i>SbFL9.1</i>
Q_PH_7_76	PH	7	74.28–76.69	54.7–55.2	21.9	(–37; 69) (cm)	16	<i>qHT7.1</i> , (<i>Dw3</i>)
Q_NL_7_78	NODE_L	7	76.29–79.59	55.1–55.8	29.9	(–0.1; 4.2) (cm)	14	<i>qHT7.1</i> , (<i>Dw3</i>)
Q_PED_7_78	PED	7	74.8–82.1	54.84–56.26	12.6	(–8; 10) (cm)	21	<i>qHT7.1</i> , (<i>Dw3</i>)
Q_NL_7_98	NODE_L	7	96.1–100.7	58.3–59.1	11.8	(–5.8–4.2) (cm)	9	<i>Dw3</i>
Q_PH_7_106	PH	7	102–108.3	59.4–60.7	7.6	(–14; 58) (cm)	15	<i>Dw3</i>

(QTL_FL_9_105) potentially close to the *SbFL9.1* gene (Higgins et al. 2014; Bouchet et al. 2017).

A strong QTL for PH has been detected on chromosome 7 around 75 cM (QTL_PH_7_76) with significance in the GR2013 and KK2013 subpopulations. This QTL colocalized with a highly significant QTL for NODE_L (QTL_NL_7_78) and a strong and highly consistent QTL for PED (QTL_PED_7_78). Nearby this QTL, another QTL (QTL_PH_7_106) also had a large effect on PH and colocalized with a large effect QTL for NODE_L (QTL_NL_7_98). The QTL region of chromosome 7 could be related to 1 or 2 genes. The main candidate gene is *Dw3* (Multani et al. 2003; Brown et al. 2008). However, according to Li et al. (2015), chromosome 7 could harbor 2 genes: *qHT7.1*, positioned before *Dw3*, may influence both stem length and peduncle length, while *Dw3* may only influence stem length.

Complex QTL effect pattern at large effect QTL

QTL with large effects showed complex patterns with effects distributed over many parents and a wide range of effects modulated by the genetic background and the environment. Almost all parental alleles had at least 1 significant EC interaction. Such a complex pattern can be illustrated for QTL_FL_3_78 (Fig. 3). First, we noticed the contrasting parental effects with parents like CSM417 or CSM388 whose alleles reduced maturity, while IS15401 alleles increased it. Then, we observed differences in expression due to the genetic backgrounds. For example, the allele of Fara-Fara had a small effect in a GR background, while it strongly increased maturity in the LT and KK backgrounds. Finally, we also observed environmental differences, like the stronger cycle reduction of the CSM388 allele in 2012 compared to 2013.

QTL effect on photoperiodism

The plots of Fig. 4a–c represents QTL allele additive effects for a given photoperiod compared to the recurrent (reference) parent. QTL_FL_6_3 (*Ma6*) was the QTL with the highest proportion of alleles influenced by the photoperiod (Fig. 4a). At that position

compared to GR, the effects of E36-1 or B35 were negatively affected by the photoperiod. Those alleles reduced the photoperiod sensitivity. When the days were longer (e.g. at the first sowing date ~12.5 h) a genotype carrying those alleles increased its cycle less than a genotype carrying the allele of the central parent. QTL_FL_6_38 (*Ma1*) was also sensitive to photoperiod with 5 parental alleles interacting significantly with the photoperiod over the different genetic backgrounds. For example, in GR2012, the allele of White Kaura increased the photoperiod sensitivity compared to the recurrent parent (Fig. 4b).

At QTL_FL_3_78 (*Elf3*, Fig. 4c), the parental alleles were mostly insensitive to photoperiod. We only detected significant effects of the photoperiod for 3 alleles. The alleles of Fara-Fara and IS15401 had a reduced sensitivity, while the allele of B35 increased it. The alleles of QTL_FL_9_105 (*SbFL9.1*) were also insensitive to the photoperiod with only 2 significant interactions. Even though the EC range looks small (0.3 h), it caused important variations of the QTL effect. For example, at QTL_FL_6_36, the effect of an SC566-14 allele varied by 60 dd (around 3 days; Fig. 4b).

Dissecting PH genetic determinism

The phenotypic data for PH and its components (NODE_N, NODE_L, PED, PAN) allowed us to dissect PH genetic architecture. PH can be expressed as $PH = (NODE_N * NODE_L) + PED + PAN$. Since the phenotypic values of NODE_N are strongly correlated with FLAG, it was not surprising to find overlapping QTL for the 2 traits on chromosomes 3 and 6 (QTL_NN_3_78, QTL_NN_6_2). In terms of photoperiod sensitivity, the QTL for NODE_N followed a similar pattern to the ones from FLAG. QTL_NN_3_78 (*Elf3*) was rather insensitive to photoperiod with 4 parental alleles having a significant interaction, while QTL_NN_6_2 (*Ma6*) was more sensitive with 6 alleles with significant interactions with the photoperiod (e.g. Malisor 84-7).

We also observed a strong agreement between the QTL positions detected for PH and NODE_L on chromosome 7. QTL_PH_7_76 and QTL_NL_7_78 (*qHT7.1*) colocalized, while

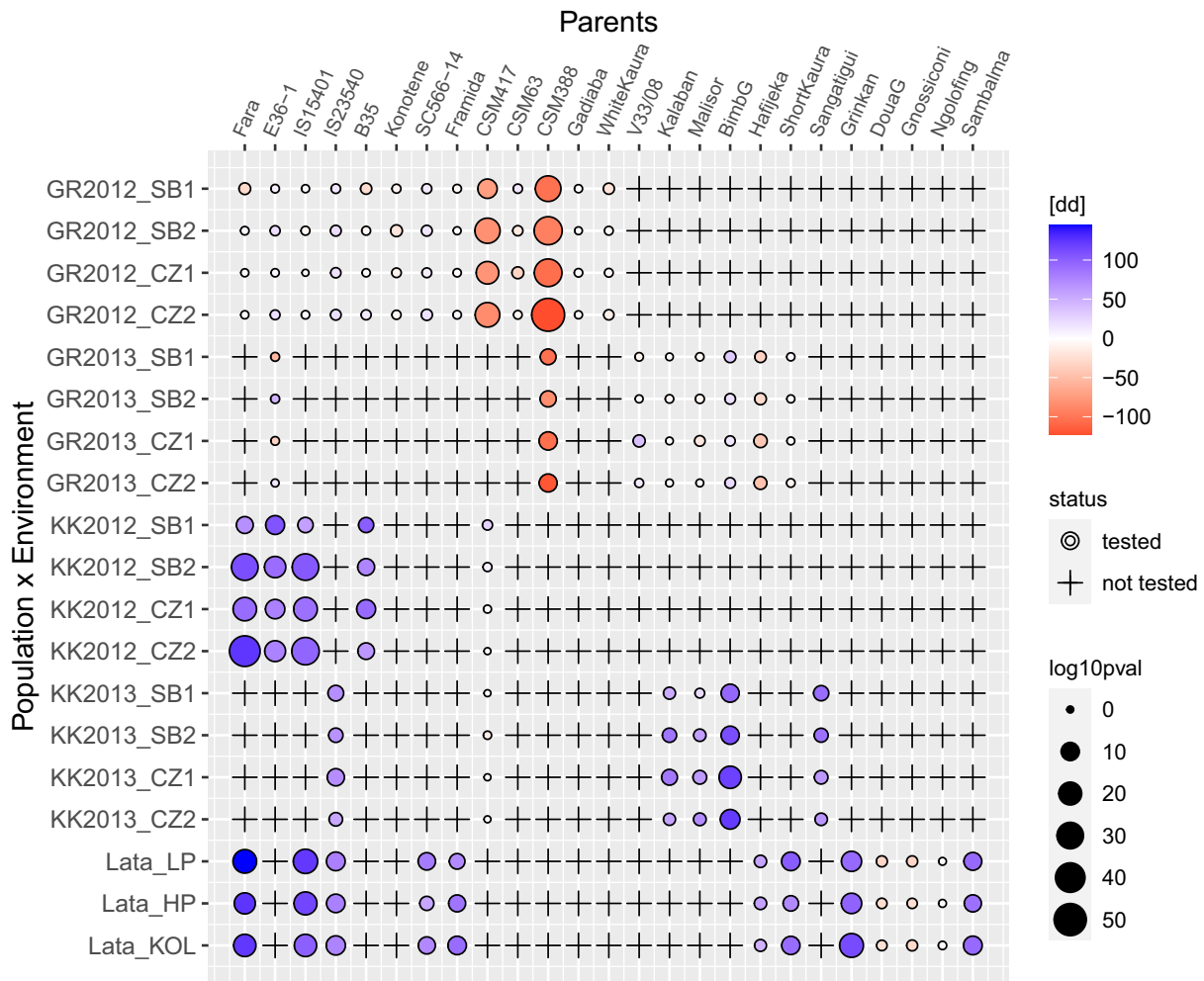


Fig. 3. Estimated QTL allelic effect given environment and genetic background for flag leaf appearance using model 2 at chromosome 3 position 77.3 cM. X axis: donor parents. Y axis: genetic backgrounds (GR, KK, LT) and environments (SB1-2: Sotuba sowing 1 and 2, CZ1-2: Cinzana sowing 1 and 2, LP/HP: low/high phosphorus, KOL: Kolombada). The color is proportional to the effect size and the circle size to its significance. Crosses represent untested allelexbackgroundxenvironment combinations.

QTL_PH_7_106 and QTL_NL_7_98 (Dw3) were separated by less than 10 cM. The QTL influencing NODE_L were not sensitive to photoperiod, but other ECs like VPD or potential ETP modulated the parental allelic effects at those positions. For example, at QTL_PH_7_76, the effects of parents like Hafijeka or Short Kaura were reduced when VPD increased (Fig. 4e). Surprisingly, the corresponding QTL (QTL_PH_7_76) detected for PH showed significant interaction with the photoperiod (Fig. 4d) in the GR subpopulations. We consider that this apparent effect of photoperiod on QTL_PH_7_76, is due to the fact that PH is proportional to the interaction NODE_N * NODE_L. Therefore, at chromosome 7, the signal is due to the interaction between a photoperiod-sensitive component (NODE_N) and a photoperiod-insensitive part (NODE_L). We hypothesize that the apparent photoperiod sensitivity of QTL_PH_7_76 is due to the NODE_N component of the height that is strongly photoperiod-sensitive, for example via the QTL on chromosome 6 (QTL_NN_6_2).

For PED, QTL_PED_7_78 (*qHT7.1*) was the most environmentally sensitive QTL. This QTL was not photoperiod-sensitive, but covariables like SVP had a negative effect on the propensity to increase PED compared to the reference parent. This effect was consistent in the GR2013 subpopulation with 5 parents (V33/08, BimbG,

Kalaban, Hafijeka, and Short Kaura) reducing their propensity to increase PED when SVP increased (Fig. 4f). It is interesting to emphasize that drought-related ECs (VPD, SVP) influenced both QTL_PH_7_76 and QTL_PED_7_78 with effects going in the same direction.

Expected QTL effect beyond the tested environments

Between 12 and 13.75 degrees of latitude, the Malian environment is characterized by a southwest-to-northeast gradient (Supplementary Fig. 2). The southwest is cooler with lower temperature ranges, higher precipitation, and humidity, while the northeast is drier with higher temperature ranges and lower precipitations. A final extension of our results is the projection of QTL allelic effects having a significant interaction with 1 of the ECs in the Malian environment. For that we substituted the observed EC values from a grid of 60 points in the estimated allele sensitivity equation (Fig. 5). Those results represent the expected QTL allele additive effect given the new EC conditions with respect to the central parent in the environment with the lowest EC value.

In Fig. 4d and f, we represented the expected behavior of the BimbG and V33/08 alleles at QTL_PH_7_76 and QTL_PED_7_78,

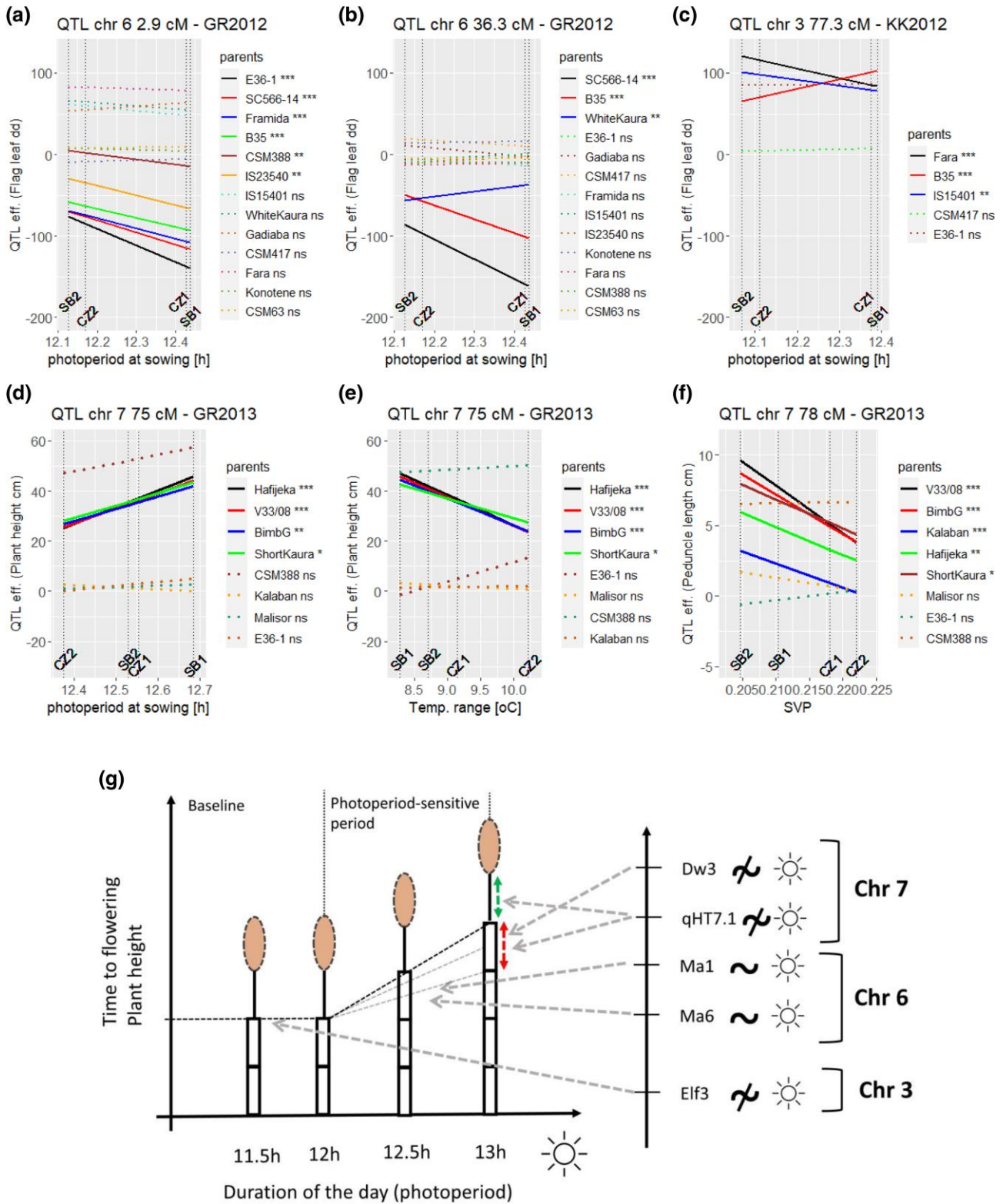


Fig. 4. Sensitivity of the QTL parental allele effects to environmental covariables calculated with model (4). Each slope is described by $\hat{\alpha}_p + EC_j * \hat{S}_p$, with $\hat{\alpha}_p$ representing the main allelic additive effect and \hat{S}_p the sensitivity to increase in the environmental covariate (EC_j). a) Flag leaf QTL chr 6 (3 cM) in GR2012 given photoperiod; b) Flag leaf QTL chr 6 (36.3 cM) in GR2012 given photoperiod; c) Flag leaf QTL chr 3 (77.3 cM) in KK2012 given photoperiod. d) PH QTL chr 7 (76 cM) in GR2013 given photoperiod. e) PH QTL chr 7 (76 cM) in GR2013 given temperature range. f) Peduncle length QTL chr 7 (78 cM) in GR2013 given SVP. g) Illustration of the relationship between flowering time, PH, and photoperiod with influential genomic regions on the right side. Flowering time can be seen as a broken linear function with a constant baseline period and a photoperiod-sensitive period when time to flowering increases with photoperiod. Plants with early (late) flowering time due to an extended baseline period (Elf3) and/or an increased photoperiod sensitivity (Ma6, Ma1) become shorter (taller) due to the accumulation of fewer (more) internodes (Elf3, Ma6) whose average size (red arrow, qHT7.1, Dw3) is not influenced by the photoperiod. The peduncle length (green arrow) is also not photoperiod-sensitive (qHT7.1).

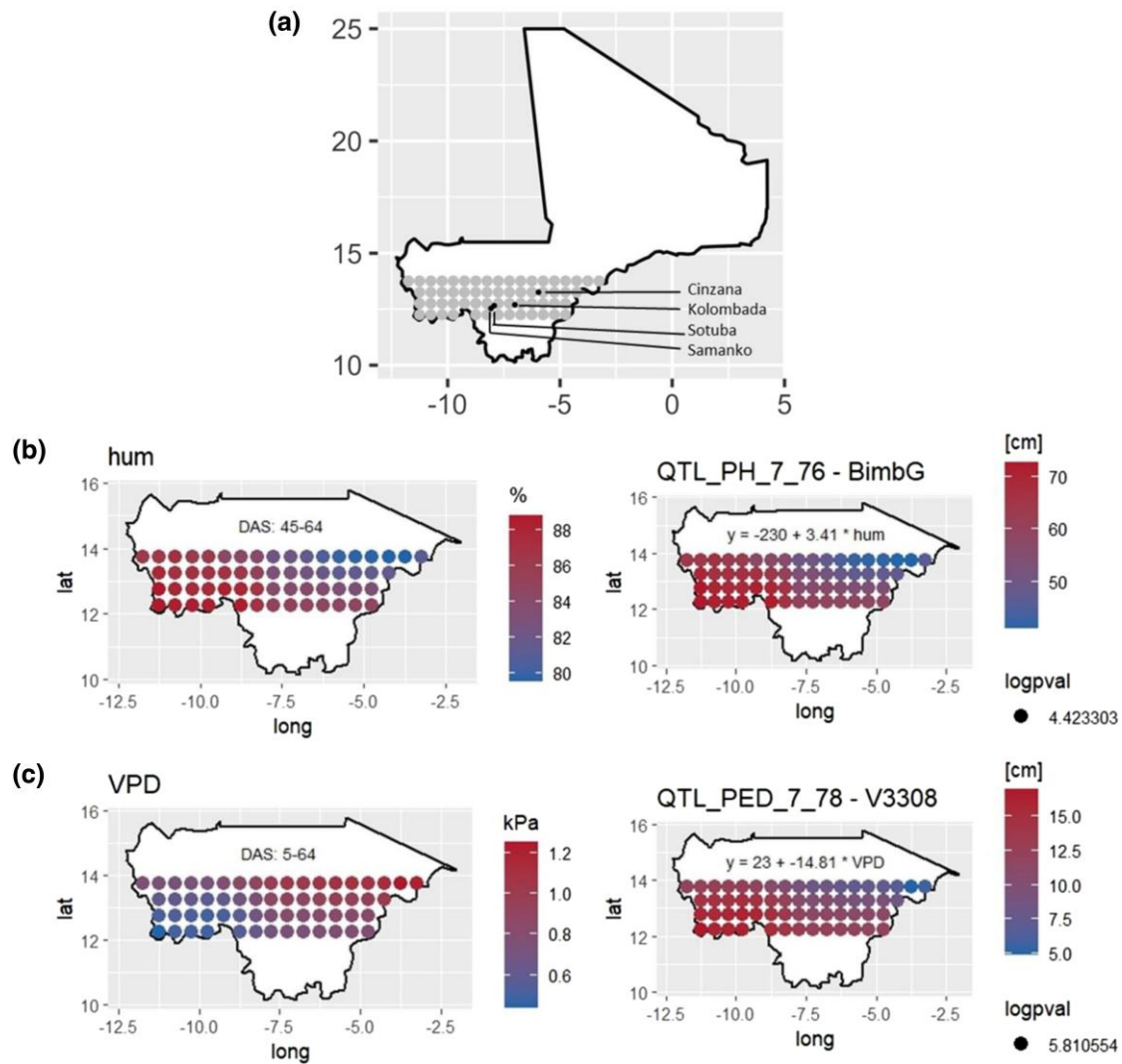


Fig. 5. Extrapolating the QTL by EC at the Malian scale a) map of Mali with testing locations and neighboring areas of projection. b and c) Projections of additive QTL allelic effects given allelic sensitivity and new VPD and humidity conditions. The effect must be interpreted as the deviation with respect to the central parent in the environment with the lowest EC value. QTL positions: b) QTL_{PH_7_76} BimbG×humidity; and c) QTL_{PED_7_78} V33/08×VPD. The projections were obtained by substituting observed environmental covariables in a grid of 60 points of the Malian environment in QTL allele sensitivity equations.

respectively. The BimbG allele was positively influenced by humidity, which increases its effect on PH in the more humid southwest and reduces it in the drier northeast regions (Fig. 5b). Figure 5c illustrates the effect of VPD on the effect of the V33/08 allele at QTL_{PED_7_78} on PED extension. PED extension was reduced in the northeast drier regions, while it was increased in the more humid southwest part of Mali. We can emphasize that those 2 alleles react similarly to the environmental gradient by increasing PH more in the southwest.

Discussion

The main objectives of this work were the introduction of a new sorghum genetic resource and a new statistical methodology to dissect QTL×E interactions. Here, we emphasize the properties of the Western and Central Africa BCNAM design and of the proposed statistical methodology, which constitute a lever to support the development of improved varieties. Although grain yield and GWGH have been analyzed, only a limited set of QTL and QTL×E interactions have been identified for those traits. This

likely results from a lack of power due to a too small set of experiments combined with moderate broad-sense heritability of these traits. In this context, the final sections of the discussion are focused on flowering time and PH, 2 traits well recognized as key components of the adaptation to local abiotic conditions (Buckler et al. 2009; Moles et al. 2009).

Multireference BCNAM design properties

A major contribution of this work is the development of a new sorghum genetic resource taking the form of a multireference BCNAM design. Its usefulness can be evaluated given criteria like genetic diversity, mapping power and resolution, and potential for genetic gains. In terms of diversity exploration, the use of 3 recurrent parents instead of one, as in almost all the (BC)NAM populations, substantially increases the exploitable genetic diversity. This extra diversity increases the contrast between the recurrent and the donor parent, which should help to detect significant genetic regions and estimate their environmental sensitivity.

In terms of QTL detection, the usefulness of a design can be evaluated in terms of detection power, capacity to estimate and

trace the QTL effect, and mapping resolution. The power gain offered by the NAM design compared to biparental populations (Li et al. 2011) or association panels (Bouchet et al. 2017) has already been demonstrated. This should also be valid for our population. The most relevant advantage of a multireference BCNAM design is the possibility to test allelic effects in several genetic backgrounds. Similarly to Christopher et al. (2021), we show that the parent allelic effect can be strongly modulated by the genetic background (Fig. 3). More generally, in terms of QTL effect characterization, MPPs like the (BC)NAM designs increase the allele frequencies and allow the user to trace back the allelic effect to a specific parent (Myles et al. 2009). Analyzed properly, such data allow the precise estimation of the parental allelic effect, which is fundamental for breeding applications.

The main disadvantage of the (BC)NAM design is the low mapping resolution compared to designs involving further intercrossing like MAGIC (Klasen et al. 2012). Even though the (BC)NAM design involves more recombination than biparental populations, the recombinations are still restricted within a cross, which considerably extends the linkage disequilibrium decay (Garin et al. 2021). The combination of our design with strategies like RapMap (Zhang et al. 2021) could improve the resolution. In terms of genetic gain, Bernardo (2021) showed that populations like MAGIC do not have a significant advantage compared to multiple cross populations like the BCNAM. Designs like the (BC)NAM population can also increase the prediction ability of untested lines in genomic selection schemes due to the genetic relatedness between lines composing the population (Lehermeier et al. 2014).

A last question related to the multireference BCNAM design optimization is the need to cross all donor parents to the recurrent parents (full factorial) or only a subset. On the one hand, by performing all crosses we improve our ability to estimate QTL allelic effects in multiple genetic backgrounds and determine the stability of those effects. On the other hand, given a fixed total population size, the use of a partial factorial design could increase the individual cross sizes, which increases the QTL detection power (Garin et al. 2021). Reducing the number of crosses per parent could also increase the number of parents included in the design and therefore the addressed genetic diversity. Given that the estimation of the QTL effect is conditioned by its detection, we consider that performing only a selected number of crosses in a multireference (BC)NAM design could be an interesting strategy to increase the QTL detection power and/or diversity. More definitive answers regarding the optimization of multireference BCNAM designs could be obtained by simulations.

Statistical methodology properties and limitations

In this work, we propose an approach allowing the integration of high-resolution environmental information in MPP-ME QTL analyses to improve our understanding of the GxE interaction. Few alternative approaches analyze this kind of data (e.g. De Walsche et al. 2023). We propose a sequential strategy to identify parental alleles exhibiting GxE interactions and decompose them into environmental covariate sensitivity curves. We used a mixed model with unstructured VCOV structure to control for the genetic (co)variance and performed an approximate model estimation for the QTL scan. However, we performed an exact model estimation of the QTL effects and their interaction with the environment. Such a joint effect estimation could be more precise than the meta-analysis of a single environment proposed by De Walsche et al. (2023).

The main limitation to illustrate our approach was the number of available environments, especially for the QTLxE sensitivity

estimation. Even if the selected environments cover a broad variability, their reduced number limits the statistical inference of our models. From a general point of view, 2 environments are sufficient to estimate QTL effect variations. However, our extension of the QTLxE effect to estimate its sensitivity to the environmental covariates requires that each genotype be observed in a number of conditions that are large enough to estimate the sensitivity curve parameters. Statistically, the available degrees of freedom to estimate the $\hat{\alpha}_p$ and \hat{S}_p terms are equal to $N_{env} - 2$. This forced us to test for a maximum of 1 EC at a time, and to interpret our results with caution. Our strategy still allowed us to establish whether the QTL environmental variation could be explained by some of the ECs, but it was often difficult to make precise distinctions between several ECs showing similar degrees of correlation with the QTL effect variation.

The combination of genetic analysis and crop modeling is an alternative and complementary approach. The construction of a genotype-to-phenotype (G2P) set-up integrating QTL expression of crop model parameters potentially allows the extrapolation of the QTL effect to any environment (Reymond et al. 2003). Such a G2P set-up can support the design of new ideotypes (Gu et al. 2014), and the prediction of new genotype behavior in future climate scenarios (Kadam et al. 2019). This strategy builds on the knowledge accumulated in the crop model to reconstruct the GxE interaction, while our QTLxE approach is based on less complex physiological relationships derived from observed data that make the prediction dependent on the observed conditions (Bustos-Korts et al. 2016). However, the success of the G2P approach is based on the identification of less complex physiological mechanisms that are stable across environments (Tardieu 2003). The crop model parameters are often difficult to phenotype and require controlled environments that strongly differ from natural conditions (Gu et al. 2014).

Variations in flowering time genetic architecture and its GxE component

Our method helped us to gain insight into the genetic architecture of flowering time in the emerging C4 model sorghum. Our results showed that, in this experimental design, flowering time was controlled by 3–4 QTL with very strong effects. Those effects were consistent in most of the genetic backgrounds and environments but could be strongly modulated by ECs, especially the photoperiod. Those observations strongly contrast with those of Mace et al. (2013), who observed that flowering time was controlled by many small loci with a low proportion of GxE due to the temperature rather than the photoperiod.

Despite important similarities with Mace et al. (2013), like the use of a similar BCNAM design covering a large genetic diversity and the characterization in a large spectrum of environments producing important phenotypic differences, the selection applied during the population development and the statistical methodology can explain observed differences. Compared to us, Mace et al. (2013) applied a stronger control of the flowering time range during the development of their population. They considered that this selection strongly reduced the effect of important genes involved in the photoperiod pathway like Ma1, which can explain why most of the detected genomic regions were involved in the temperature pathway and the reduction of the observed GxE interaction. Our moderate control of flowering time certainly allowed the preservation of strong allelic effects involved in the photoperiod pathway.

Next to the differences in selection pressure, we also want to emphasize the difference in terms of statistical approach used.

We estimated models using within-environment adjusted means, while Mace *et al.* (2013) used across-environment adjusted means which do not allow the estimation of QTLxEC effects (Garin *et al.* 2020). Even though we estimated a strong heritability for flowering time, which as in Mace *et al.* (2013) indicates a low level of GxE, our QTLxEC model still allowed us to detect important modulation of QTL effects by ECs like the photoperiod.

Using our QTLxEC models, we could further characterize the genetic basis of flowering time. For example, we could illustrate the photoperiod-insensitive nature of QTL_3_FL_78 (*Elf3*; same result as Guillon *et al.* 2018) and QTL_FL_9_105 (*SbFL9.1*) which only influenced the baseline duration. On the other hand, the QTL on chromosome 6 (QTL_FL_6_3 and QTL_FL_6_38) linked to the Ma6 and Ma1 regions influenced the baseline flowering duration, but also had effects influenced by the photoperiod, which makes them a source of photoperiod sensitivity (Fig. 4g). QTL_FL_6_3 (Ma6) was mostly influenced by the radiation covariables (photoperiod, observed hours of sun, and solar radiation), which support the hypothesis of Ma6 being part of the photoperiod pathway (Takai *et al.* 2012). Concerning the Ma6 region, we should also emphasize that, according to the original hypothesis of Rooney (1999), it is supposed to influence flowering time in an epistatic way with the Ma5 gene, located on chromosome 2 (Mace and Jordan 2010). We detected a strong signal in the region of Ma6, but only a mild signal on chromosome 2 (Ma5 region) in the GR subpopulation tested in 2012. This absence of signal on chromosome 2 could be due to a fixation of the Ma5 gene to the favorable allele in our subpopulations, or to the fact that in our population Ma6 mostly affects flowering time independently of other genomic regions.

Finally, we observed that QTL_FL_6_38 (Ma1) was significantly influenced by both photoperiod-related ECs and the temperature range. In our trials, the temperature range was strongly influenced by the sowing date (i.e. the photoperiod), therefore it is difficult to disentangle their respective effects. We still hypothesize that QTL_FL_6_38 (Ma1) is part of the photoperiod pathway (Childs *et al.* 1997; Rooney 1999; Higgins *et al.* 2014), but it is possible that temperature also influences this genomic region.

PH components and their interactions with the environment

Our genetic resources and methodology helped us to gain knowledge about genetic regions strongly influencing PH. We showed that, in the considered design, PH was almost exclusively influenced by 2 QTL on chromosome 7 (QTL_PH_7_76 and QTL_PH_7_106). Those QTL cover the regions of the previously identified candidate genes *qHT7.1* and *Dw3* (Li *et al.* 2015; Bouchet *et al.* 2017). The decomposition of PH into the number and length of internodes, peduncle length, and panicle length showed that PH is controlled by phenology-dependent mechanisms influencing the number of internodes and phenology-independent genes controlling the length of the internode. The colocalization of QTL for the number of internodes and flag leaf appearance on chromosome 3 (QTL_FL_3_78 and QTL_NN_3_78) and 6 (QTL_FL_6_3 and QTL_NN_6_3) illustrates the connection of PH and plant cycle via the potential pleiotropic action of the *Elf3* candidate gene region Ma6, and to a lesser extent Ma1. The genetic association between flowering time and the number of internodes makes sense because internode organogenesis is a function of the plant cycle (Takai *et al.* 2012; Fig. 4g). Given sufficient nutrients, longer maturity allows the plant to accumulate more internodes.

Other important genetic determinants of PH were located on chromosome 7 with very strong effects on the length of the internode (QTL_NL_7_78 and QTL_NL_7_98) and on the peduncle

length (QTL_PED_7_78). Our data support the results of Li *et al.* (2015) concerning the existence of 2 distinct genes (*qHT7.1* and *Dw3*) because the QTL effects of chromosome 7 were detected at different positions (around 75 cM and 100 cM) in different populations. The phenotypic effects of those positions were also consistent with the observations of Li *et al.* (2015) because the 75 cM position influenced both internode length and peduncle length, while the 100 cM position only influenced internode length. The genomic region controlling the length of the internode and the peduncle length interacted significantly with a large number of ECs. Contrary to the flowering time QTL, the QTLxEC pattern was more heterogeneous with parental alleles interacting with drought-related ECs like VPD, SVP, and humidity- or temperature-related ECs like minimum temperature or cumulated degree days. The sensitivity of sorghum peduncle length to humidity was already detected by Klein *et al.* (2001).

Developing climate-smart varieties

The precise characterization of the genetic architecture of flowering time and PH for given environmental constraints could support the development of climate-smart varieties. We showed that adaptation mechanisms are controlled by large effects of QTL related to identified genes and candidate genes, but, like other studies, our analyses revealed that the effects of those QTL positions were distributed over many parental alleles with differences of expression given the genetic background (Mace *et al.* 2013; Higgins *et al.* 2014; Christopher *et al.* 2021). The possibility of estimating a wide range of parental effects in the WCA-BCNAM population enables the use of allelic effects for different breeding applications. For example, changing the duration of the cycle without affecting the photoperiod sensitivity (e.g. QTL_FL_3_78 CSM417: -80 dd) or varying PH via the internode length independently of the environment (e.g. QTL_NL_7_78 IS23540: +3.1 cm). All results including QTL allelic effect sensitivity were compiled in an R application (sorghum QTL effects - SQE) to facilitate their use by geneticists and sorghum breeders (<https://github.com/vincentgarin/SQE>).

Conclusion

We present here a large multireference BCNAM design with unprecedented coverage of the sorghum genetic diversity of WCA. We developed a multiparent multi-environment QTL methodology that was applied to analyses of flowering time and PH that allowed us to confirm the existence of genomic regions with strong effects, like Ma1, Ma6, or *Dw3*. The integration of ECs in the QTLxEC detection model allowed the identification of genomic regions covering Ma6 and Ma1 that are photoperiod-sensitive, while the region on chromosome 3 covering the possible candidate gene *Elf3* is photoperiod-insensitive. We also reached a better understanding of PH construction through the identification of photoperiod-insensitive regions impacting the number of internodes (*Elf3*) and the internode size (*dw3*, *qHT7.1*) and photoperiod-sensitive regions contributing to the number of internodes (Ma1).

Data availability

The genotypic and phenotypic data are available here <https://doi.org/10.18167/DVN1/TZVGLS>. The scripts to reproduce the results are available here https://gitlab.cirad.fr/agap/giv/sorghum_bcnam_analysis. The results were gathered into an interactive database available here <https://github.com/vincentgarin/SQE>.

For plant material, please contact the corresponding authors for availability.

[Supplemental material](#) available at GENETICS online.

Acknowledgments

The authors thank Madina Diancoumba and Jan Jarolímek for providing the environmental data that were used to perform the projection in the Malian environment. We also thank Jean-Christophe Glaszmann and the AdaptGrass project for the access to the sorghum whole-genome sequence data.

Funding

This work was supported by a grant from the Generation Challenge Programme (Project Numbers G7010.05.01 and G7010.05.02). The work of Vincent Garin was supported by a grant from the Swiss National Science Foundation (Postdoc.Mobility grant no: P500PB_203030). Dr Kholová's contribution was financed by an internal grant agency of the Faculty of Economics and Management at the Czech University of Life Sciences Prague (Grant Life Sciences 4.0 Plus no. 2022B0006)

Conflicts of interest

The authors declare no conflicts of interest.

Literature cited

- Altendorf KR, Larson SR, DeHaan LR, Crain J, Neyhart J, Dorn KM, Anderson JA. 2021. Nested association mapping reveals the genetic architecture of spike emergence and anthesis timing in intermediate wheatgrass. *G3 (Bethesda)*. 11(3):jkab025. doi:[10.1093/g3journal/jkab025](https://doi.org/10.1093/g3journal/jkab025).
- Andrews DJ. 1973. Effects of date of sowing on photosensitive Nigerian sorghums. *Exp Agric*. 9(4):337–346. doi:[10.1017/S0014479700010139](https://doi.org/10.1017/S0014479700010139).
- Annicchiarico P. 2002. Genotype × Environment Interactions: Challenges and Opportunities for Plant Breeding and Cultivar Recommendations. *FAO Plant Production and Protection Paper No. 174*. Rome: FAO.
- Bardol N, Ventelon M, Mangin B, Jasson S, Loywick V, Couton F, Derue C, Blanchard P, Charcosset A, Moreau L. 2013. Combined linkage and linkage disequilibrium QTL mapping in multiple families of maize (*Zea mays* L.) line crosses highlights complementarities between models based on parental haplotype and single locus polymorphism. *Theor Appl Genet*. 126(11):2717–2736. doi:[10.1007/s00122-013-2167-9](https://doi.org/10.1007/s00122-013-2167-9).
- Bauer E, Falque M, Walter H, Bauland C, Camisan C, Campo L, Meyer N, Ranc N, Rincenc R, Schipprack W, et al. 2013. Intraspecific variation of recombination rate in maize. *Genome Biol*. 14(9):R103. doi:[10.1186/gb-2013-14-9-r103](https://doi.org/10.1186/gb-2013-14-9-r103).
- Bernardo R. 2016. Bandwagons I, too, have known. *Theor Appl Genet*. 129(12):2323–2332. doi:[10.1007/s00122-016-2772-5](https://doi.org/10.1007/s00122-016-2772-5).
- Bernardo R. 2021. Multiparental populations in line development: genetic gain, diversity, and practical limitations. *Crop Sci*. 61(6):4139–4150. doi:[10.1002/csc2.20632](https://doi.org/10.1002/csc2.20632).
- Boer MP, Wright D, Feng L, Podlich DW, Luo L, Cooper M, van Eeuwijk FA. 2007. A mixed-model quantitative trait loci (QTL) analysis for multiple-environment trial data using environmental covariables for QTL-by-environment interactions, with an example in maize. *Genetics*. 177(3):1801–1813. doi:[10.1534/genetics.107.071068](https://doi.org/10.1534/genetics.107.071068).
- Bouchet S, Olatoye MO, Marla SR, Perumal R, Tesso T, Yu J, Tuinstra M, Morris GP. 2017. Increased power to dissect adaptive traits in global Sorghum diversity using a nested association mapping population. *Genetics*. 206(2):573–585. doi:[10.1534/genetics.116.198499](https://doi.org/10.1534/genetics.116.198499).
- Bradbury PJ, Zhang Z, Kroon DE, Casstevens TM, Ramdoss Y, Buckler ES. 2007. TASSEL: software for association mapping of complex traits in diverse samples. *Bioinformatics*. 23(19):2633–2635. doi:[10.1093/bioinformatics/btm308](https://doi.org/10.1093/bioinformatics/btm308).
- Broman KW. 2022. A generic hidden Markov model for multiparent populations. *G3 (Bethesda)*. 12(2):jkab396. doi:[10.1093/g3journal/jkab396](https://doi.org/10.1093/g3journal/jkab396).
- Brown PJ, Rooney WL, Franks C, Kresovich S. 2008. Efficient mapping of plant height quantitative trait loci in a Sorghum association population with introgressed dwarfing genes. *Genetics*. 180(1):629–637. doi:[10.1534/genetics.108.092239](https://doi.org/10.1534/genetics.108.092239).
- Browning BL, Zhou Y, Browning SR. 2018. A one-penny imputed genome from next-generation reference panels. *Am J Hum Genet*. 103(3):338–348. doi:[10.1016/j.ajhg.2018.07.015](https://doi.org/10.1016/j.ajhg.2018.07.015).
- Buckler ES, Holland JB, Bradbury PJ, Acharya CB, Brown PJ, Browne C, Ersoz E, Flint-Garcia S, Garcia A, Glaubitz JC, et al. 2009. The genetic architecture of maize flowering time. *Science*. 325(5941):714–718. doi:[10.1126/science.1174276](https://doi.org/10.1126/science.1174276).
- Bustos-Korts D, Malosetti M, Chapman S, van Eeuwijk F. 2016. Modelling of genotype by environment interaction and prediction of complex traits across multiple environments as a synthesis of crop growth modelling, genetics and statistics. *Crop Syst Biol*. 55–82. doi:[10.1186/s12918-016-0289-9](https://doi.org/10.1186/s12918-016-0289-9).
- Campbell DR, Waser NM. 2001. Genotype by environment interaction and the fitness of plant hybrids in the wild. *Evolution*. 55(4):669–676. doi:[10.1554/0014-3820\(2001\)055\[0669:gbeiat\]2.0.co;2](https://doi.org/10.1554/0014-3820(2001)055[0669:gbeiat]2.0.co;2).
- Cavanagh C, Morell M, Mackay I, Powell W. 2008. From mutations to MAGIC: resources for gene discovery, validation and delivery in crop plants. *Curr Opin Plant Biol*. 11(2):215–221. doi:[10.1016/j.pbi.2008.01.002](https://doi.org/10.1016/j.pbi.2008.01.002).
- CEDEAO-UEMOA-CILSS. 2016. Catalogue Régional des Espèces et Variétés Végétales CEDEAO-UEMOA-CILSS.
- Chantereau J, Ag Hamada M, Bretauudeau A, Tembely S. 1998. Etude de Nouvelles Variétés de Sorgho en Milieu Paysan Dans la Zone Cotonnière Cmdt au Mali (1995–1996). Montpellier: CIRAD.
- Chen Q, Yang CJ, York AM, Xue W, Daskalska LL, DeValk CA, Krueger KW, Lawton SB, Spiegelberg BG, Schnell JM, et al. 2019. TeoNAM: a nested association mapping population for domestication and agronomic trait analysis in maize. *Genetics*. 213(3):1065–1078. doi:[10.1534/genetics.119.302594](https://doi.org/10.1534/genetics.119.302594).
- Childs KL, Miller FR, Cordonnier-Pratt MM, Pratt LH, Morgan PW, Mullet JE. 1997. The sorghum photoperiod sensitivity gene, Ma3, encodes a phytochrome B. *Plant Physiol*. 113(2):611–619. doi:[10.1104/pp.113.2.611](https://doi.org/10.1104/pp.113.2.611).
- Christopher M, Paccapelo V, Kelly A, Macdonald B, Hickey L, Richard C, Verbyla A, Chenu K, Borrell A, Amin A, et al. 2021. QTL identified for stay-green in a multi-reference nested association mapping population of wheat exhibit context dependent expression and parent-specific alleles. *Field Crops Res*. 270:108181. doi:[10.1016/j.fcr.2021.108181](https://doi.org/10.1016/j.fcr.2021.108181).
- Clément JC, Leblanc JM. 1980. Prospection des mils pénicillaires, sorghos et graminées mineures en Afrique de l'Ouest. Campagne 1978. République du Mali. Orstom éditions. Paris: International Board for Plant Genetic Resources.
- Cobb JN, Biswas PS, Platten JD. 2019. Back to the future: revisiting MAS as a tool for modern plant breeding. *Theor Appl Genet*. 132(3):647–667. doi:[10.1007/s00122-018-3266-4](https://doi.org/10.1007/s00122-018-3266-4).

- Costa-Neto G, Galli G, Carvalho HF, Crossa J, Fritsche-Neto R. 2021. EnvRtype: a software to interplay enviromics and quantitative genomics in agriculture. *G3* (Bethesda). 11(4):jkab040. doi:10.1093/g3journal/jkab040.
- Crouse WL, Kelada SNP, Valdar W. 2020. Inferring the allelic series at QTL in multiparental populations. *Genetics*. 216(4):957–983. doi:10.1534/genetics.120.303393.
- Des Marais DL, Hernandez KM, Juenger TE. 2013. Genotype-by-environment interaction and plasticity: exploring genomic responses of plants to the abiotic environment. *Annu Rev Ecol Evol Syst*. 44(1):5–29. doi:10.1146/annurev-ecolsys-110512-135806.
- De Walsche A, Vergne A, Rincet R, Roux F, Nicolas SD, Welcker C, Mezrouk S, Charcosset A, Mary-Huard T. 2023. metaGE: Investigating Genotype-by-Environment interactions through meta-analysis. *bioRxiv* 530237. <https://doi.org/10.1101/2023.03.01.530237>, preprint: not peer reviewed.
- Diallo C, Rattunde HFW, Gracen V, Touré A, Nebié B, Leiser W, Dzidzienyo DK, Sissoko I, Danquah EY, Diallo AG, et al. 2019. Genetic diversification and selection strategies for improving Sorghum grain yield under phosphorous-deficient conditions in West Africa. *Agronomy*. 9(11):742. doi:10.3390/agronomy9110742.
- Diouf I, Derivot L, Koussevitzky S, Carretero Y, Bitton F, Moreau L, Causse M. 2020. Genetic basis of phenotypic plasticity and genotype-environment interactions in a multi-parental tomato population. *J Exp Bot*. 71(18):5365–5376. doi:10.1093/jxb/eraa265.
- Elshire RJ, Glaubitz JC, Sun Q, Poland JA, Kawamoto K, Buckler ES, Mitchell SE. 2011. A robust, simple genotyping-by-sequencing (GBS) approach for high diversity Species. *PLoS One*. 6(5):e19379. doi:10.1371/journal.pone.0019379.
- Falconer DS, Mackay TFC. 1996. *Introduction to Quantitative Genetics*. India: Pearson Education.
- FAO. 2008. *Catalogue ouest africain des espèces et variétés végétales*. Rome. Available from http://www.insah.org/doc/pdf/catalogue_french.pdf.
- FAO. 2023. *Global Information System*. FAO. <https://doi.org/10.18730/NMYBY>.
- Folkertsma RT, Rattunde HFW, Chandra S, Raju GS, Hash CT. 2005. The pattern of genetic diversity of Guinea-race Sorghum bicolor (L.) Moench landraces as revealed with SSR markers. *Theor Appl Genet*. 111(3):399–409. doi:10.1007/s00122-005-1949-0.
- Folliard A, Traoré PCS, Vaksman M, Kouressy M. 2004. Modeling of sorghum response to photoperiod: a threshold-hyperbolic approach. *Field Crops Res*. 89(1):59–70. doi:10.1016/j.fcr.2004.01.006.
- Fragoso CA, Moreno M, Wang Z, Heffelfinger C, Arbelaez LJ, Aguirre JA, Franco N, Romero LE, Labadie K, Zhao H, et al. 2017. Genetic architecture of a rice nested association mapping population. *G3* (Bethesda). 7(6):1913–1926. doi:10.1534/g3.117.041608.
- Gage JL, Monier B, Giri A, Buckler ES. 2020. Ten years of the maize nested association mapping population: impact, limitations, and future directions. *Plant Cell*. 32(7):2083–2093. doi:10.1105/tpc.19.00951.
- Garin V, Malosetti M, van Eeuwijk F. 2020. Multi-parent multi-environment QTL analysis: an illustration with the EU-NAM flint population. *Theor Appl Genet*. 133(9):2627–2638. doi:10.1007/s00122-020-03621-0.
- Garin V, Wimmer V, Borchardt D, Malosetti M, van Eeuwijk F. 2021. The influence of QTL allelic diversity on QTL detection in multi-parent populations: a simulation study in sugar beet. *BMC Genomic Data*. 22(1):4. doi:10.1186/s12863-021-00960-9.
- Garin V, Wimmer V, Borchardt D, Van Eeuwijk FA, Malosetti M. 2018. mppR: multi-parent population QTL analysis. Available from <https://CRAN.R-project.org/package=mppR>. R package version 1.3.0.
- Garin V, Wimmer V, Mezrouk S, Malosetti M, van Eeuwijk F. 2017. How do the type of QTL effect and the form of the residual term influence QTL detection in multi-parent populations? A case study in the maize EU-NAM population. *Theor Appl Genet*. 130(8):1753–1764. doi:10.1007/s00122-017-2923-3.
- Giraud H, Lehermeier C, Bauer E, Falque M, Segura V, Bauland C, Camisan C, Campo L, Meyer N, Ranc N, et al. 2014. Linkage disequilibrium with linkage analysis of multiline crosses reveals different multiallelic QTL for hybrid performance in the flint and dent heterotic groups of maize. *Genetics*. 198(4):1717–1734. doi:10.1534/genetics.114.169367.
- Glaubitz JC, Casstevens TM, Lu F, Harriman J, Elshire RJ, Sun Q, Buckler ES. 2014. TASSEL-GBS: a high capacity genotyping by sequencing analysis pipeline. *PLoS One*. 9(2):e90346. doi:10.1371/journal.pone.0090346.
- Goma L, Mani H, Tanimu B, Aliyu L, Garba L, Jantar H. 2012. Growth parameters of sorghum (*Sorghum bicolor* (L.) Moench) varieties as influenced by planting pattern and nitrogen rates. *Agric Soc Niger*. 609–618.
- Gu J, Yin X, Zhang C, Wang H, Struik PC. 2014. Linking ecophysiological modelling with quantitative genetics to support marker-assisted crop design for improved yields of rice (*Oryza sativa*) under drought stress. *Ann Bot*. 114(3):499–511. doi:10.1093/aob/mcu127.
- Guindo D, Teme N, Vaksman M, Doumbia M, Vilmus I, Guitton B, Sissoko A, Mestres C, Davrieux F, Fliedel G, et al. 2019. Quantitative trait loci for sorghum grain morphology and quality traits: toward breeding for a traditional food preparation of West-Africa. *J Cereal Sci*. 85:256–272. doi:10.1016/j.jcs.2018.11.012.
- Guitton B, Théra K, Tékété ML, Pot D, Kouressy M, Témé N, Rami J-F, Vaksman M. 2018. Integrating genetic analysis and crop modeling: a major QTL can finely adjust photoperiod-sensitive sorghum flowering. *Field Crops Res*. 221:7–18. doi:10.1016/j.fcr.2018.02.007.
- Hausmann B, Hess D, Reddy B, Mukuru S, Kayentao M, Welz H, Geiger H. 2001. Pattern analysis of genotype-environment interaction for striga resistance and grain yield in African sorghum trials. *Euphytica*. 122(2):297–308. doi:10.1023/A:1012909719137.
- Hemshrot A, Poets AM, Tyagi P, Lei L, Carter CK, Hirsch CN, Li L, Brown-Guedira G, Morrell PL, Muehlbauer GJ, et al. 2019. Development of a multiparent population for genetic mapping and allele discovery in six-row barley. *Genetics*. 213(2):595–613. doi:10.1534/genetics.119.302046.
- Higgins RH, Thurber CS, Assaranurak I, Brown PJ. 2014. Multiparental mapping of plant height and flowering time QTL in partially isogenic Sorghum families. *G3* (Bethesda). 4(9):1593–1602. doi:10.1534/g3.114.013318.
- Holland JB. 2007. Genetic architecture of complex traits in plants. *Curr Opin Plant Biol*. 10(2):156–161. doi:10.1016/j.pbi.2007.01.003.
- Hopkins WG. 2008. *Introduction to Plant Physiology*. Hoboken (NJ): John Wiley & Sons.
- Hung HY, Browne C, Guill K, Coles N, Eller M, Garcia A, Lepak N, Melia-Hancock S, Oropeza-Rosas M, Salvo S, et al. 2012. The relationship between parental genetic or phenotypic divergence and progeny variation in the maize nested association mapping population. *Heredity* (Edinb). 108(5):490–499. doi:10.1038/hdy.2011.103.
- Jordan DR, Mace ES, Cruickshank AW, Hunt CH, Henzell RG. 2011. Exploring and exploiting genetic variation from unadapted sorghum germplasm in a breeding program. *Crop Sci*. 51(4):1444–1457. doi:10.2135/cropsci2010.06.0326.
- Kadam NN, Jagadish SVK, Struik PC, van der Linden CG, Yin X. 2019. Incorporating genome-wide association into eco-physiological simulation to identify markers for improving rice yields. *J Exp Bot*. 70(9):2575–2586. doi:10.1093/jxb/erz120.
- Kante M, Rattunde F, Leiser W, Nebié B, Diallo B, Diallo A, Touré A, Weltzien E, Hausmann B. 2017. Can tall Guinea-race Sorghum

- hybrids deliver yield advantage to smallholder farmers in West and Central Africa? *Crop Sci.* 57(2):833–842. doi:[10.2135/cropsci2016.09.0765](https://doi.org/10.2135/cropsci2016.09.0765).
- Kante M, Rattunde F, Nebié B, Sissoko I, Diallo B, Diallo A, Toure A, Weltzien E, Haussmann B, Leiser W. 2019. Sorghum hybrids for low-input farming systems in West Africa: quantitative genetic parameters to guide hybrid breeding. *Crop Sci.* 59(6):2544–2561. doi:[10.2135/cropsci2019.03.0172](https://doi.org/10.2135/cropsci2019.03.0172).
- Kassam AH, Andrews DJ. 1975. Effects of sowing date on growth, development and yield of photosensitive sorghum at Samaru, Northern Nigeria. *Exp Agric.* 11(3):227–240. doi:[10.1017/S0014479700006761](https://doi.org/10.1017/S0014479700006761).
- Kempton RA. 1984. The design and analysis of unreplicated trials. *Vortage fur Pflanzenzuchtung.* 7:219–242.
- Kidane YG, Gesesse CA, Hailemariam BN, Desta EA, Mengistu DK, Fadda C, Pè ME, Dell'Acqua M. 2019. A large nested association mapping population for breeding and quantitative trait locus mapping in Ethiopian durum wheat. *Plant Biotechnol J.* 17(7):1380–1393. doi:[10.1111/pbi.13062](https://doi.org/10.1111/pbi.13062).
- Klasen J, Piepho H, Stich B. 2012. QTL detection power of multiparental RIL populations in *Arabidopsis thaliana*. *Heredity (Edinb).* 108(6):626–632. doi:[10.1038/hdy.2011.133](https://doi.org/10.1038/hdy.2011.133).
- Klein R, Rodriguez-Herrera R, Schlueter J, Klein P, Yu Z, Rooney W. 2001. Identification of genomic regions that affect grain-mould incidence and other traits of agronomic importance in sorghum. *Theor Appl Genet.* 102:307–319. doi:[10.1007/s001220051647](https://doi.org/10.1007/s001220051647).
- Kouressy M, Dingkuhn M, Vaksman M, Heinemann AB. 2008. Adaptation to diverse semi-arid environments of sorghum genotypes having different plant type and sensitivity to photoperiod. *Agric For Meteorol.* 148(3):357–371. doi:[10.1016/j.agrformet.2007.09.009](https://doi.org/10.1016/j.agrformet.2007.09.009).
- Kruijjer W, Boer MP, Malosetti M, Flood PJ, Engel B, Kooke R, Keurentjes JJB, van Eeuwijk FA. 2015. Marker-Based estimation of heritability in immortal populations. *Genetics.* 199(2):379–398. doi:[10.1534/genetics.114.167916](https://doi.org/10.1534/genetics.114.167916).
- Lehermeier C, Krämer N, Bauer E, Bauland C, Camisan C, Campo L, Flament P, Melchinger AE, Menz M, Meyer N, et al. 2014. Usefulness of multiparental populations of maize (*Zea mays* L.) for genome-based prediction. *Genetics.* 198(1):3–16. doi:[10.1534/genetics.114.161943](https://doi.org/10.1534/genetics.114.161943).
- Leroy T, Coumaré O, Kouressy M, Trouche G, Sidibé A, Sissoko S, Touré AO, Guindo T, Sogoba B, Dembélé F. 2014. Inscriptioin d'une variété de sorgho obtenue par sélection participative au Mali dans des projets multiacteurs.
- Li H, Bradbury P, Ersoz E, Buckler ES, Wang J. 2011. Joint QTL linkage mapping for multiple-cross mating design sharing one common parent. *PLoS One.* 6(3):e17573. doi:[10.1371/journal.pone.0017573](https://doi.org/10.1371/journal.pone.0017573).
- Li J, Ji L. 2005. Adjusting multiple testing in multilocus analyses using the eigenvalues of a correlation matrix. *Heredity (Edinb).* 95(3):221–227. doi:[10.1038/sj.hdy.6800717](https://doi.org/10.1038/sj.hdy.6800717).
- Li W, Boer MP, Zheng C, Joosen RV, Van Eeuwijk FA. 2021. An IBD-based mixed model approach for QTL mapping in multiparental populations. *Theor Appl Genet.* 134(11):3643–3660. doi:[10.1007/s00122-021-03919-7](https://doi.org/10.1007/s00122-021-03919-7).
- Li X, Guo T, Mu Q, Li X, Yu J. 2018. Genomic and environmental determinants and their interplay underlying phenotypic plasticity. *Proc Natl Acad Sci U S A.* 115(26):6679–6684. doi:[10.1073/pnas.1718326115](https://doi.org/10.1073/pnas.1718326115).
- Li X, Li X, Fridman E, Tesso TT, Yu J. 2015. Dissecting repulsion linkage in the dwarfing gene *Dw3* region for sorghum plant height provides insights into heterosis. *Proc Natl Acad Sci U S A.* 112(38):11823–11828. doi:[10.1073/pnas.1509229112](https://doi.org/10.1073/pnas.1509229112).
- Mace E, Innes D, Hunt C, Wang X, Tao Y, Baxter J, Hassall M, Hathorn A, Jordan D. 2019. The Sorghum QTL Atlas: a powerful tool for trait dissection, comparative genomics and crop improvement. *Theor Appl Genet.* 132(3):751–756. doi:[10.1007/s00122-018-3212-5](https://doi.org/10.1007/s00122-018-3212-5).
- Mace ES, Cruickshank AW, Tao Y, Hunt CH, Jordan DR. 2021. A global resource for exploring and exploiting genetic variation in sorghum crop wild relatives. *Crop Sci.* 61(1):150–162. doi:[10.1002/csc2.20332](https://doi.org/10.1002/csc2.20332).
- Mace ES, Hunt CH, Jordan DR. 2013. Supermodels: sorghum and maize provide mutual insight into the genetics of flowering time. *Theor Appl Genet.* 126(5):1377–1395. doi:[10.1007/s00122-013-2059-z](https://doi.org/10.1007/s00122-013-2059-z).
- Mace ES, Jordan DR. 2010. Location of major effect genes in sorghum (*Sorghum bicolor* (L.) Moench). *Theor Appl Genet.* 121(7):1339–1356. doi:[10.1007/s00122-010-1392-8](https://doi.org/10.1007/s00122-010-1392-8).
- Magalhaes JV, Garvin DF, Wang Y, Sorrells ME, Klein PE, Schaffert RE, Li L, Kochian LV. 2004. Comparative mapping of a major aluminum tolerance gene in sorghum and other species in the Poaceae. *Genetics.* 167(4):1905–1914. doi:[10.1534/genetics.103.023580](https://doi.org/10.1534/genetics.103.023580).
- Mahalakshmi V, Bidingger F. 2002. Evaluation of stay-green sorghum germplasm lines at ICRISAT. *Crop Sci.* 42:965. doi:[10.2135/cropsci2002.0965](https://doi.org/10.2135/cropsci2002.0965).
- Malosetti M, Voltas J, Romagosa I, Ullrich SE, van Eeuwijk FA. 2004. Mixed models including environmental covariables for studying QTL by environment interaction. *Euphytica.* 137(1):139–145. doi:[10.1023/B:EUPH.0000040511.46388.ef](https://doi.org/10.1023/B:EUPH.0000040511.46388.ef).
- Marla SR, Burwo G, Chopra R, Hayes C, Olatoye MO, Felderhoff T, Hu Z, Raymundo R, Perumal R, Morris GP. 2019. Genetic architecture of chilling tolerance in sorghum dissected with a nested association mapping population. *G3 (Bethesda).* 9(12):4045–4057. doi:[10.1534/g3.119.400353](https://doi.org/10.1534/g3.119.400353).
- Maurer A, Draba V, Jiang Y, Schnaithmann F, Sharma R, Schumann E, Kilian B, Reif JC, Pillen K. 2015. Modelling the genetic architecture of flowering time control in barley through nested association mapping. *BMC Genomics.* 16(1):290. doi:[10.1186/s12864-015-1459-7](https://doi.org/10.1186/s12864-015-1459-7).
- McMullen MD, Kresovich S, Villeda HS, Bradbury P, Li H, Sun Q, Flint-Garcia S, Thornsberry J, Acharya C, Bottoms C, et al. 2009. Genetic properties of the maize nested association mapping population. *Science.* 325(5941):737–740. doi:[10.1126/science.1174320](https://doi.org/10.1126/science.1174320).
- Moles AT, Warton DI, Warman L, Swenson NG, Laffan SW, Zanne AE, Pitman A, Hemmings FA, Leishman MR. 2009. Global patterns in plant height. *J Ecol.* 97(5):923–932. doi:[10.1111/j.1365-2745.2009.01526.x](https://doi.org/10.1111/j.1365-2745.2009.01526.x).
- Multani DS, Briggs SP, Chamberlin MA, Blakeslee JJ, Murphy AS, Johal GS. 2003. Loss of an MDR transporter in compact stalks of maize *br2* and sorghum *dw3* mutants. *Science.* 302(5642):81–84. doi:[10.1126/science.1086072](https://doi.org/10.1126/science.1086072).
- Murphy RL, Klein RR, Morishige DT, Brady JA, Rooney WL, Miller FR, Dugas DV, Klein PE, Mullet JE. 2011. Coincident light and clock regulation of pseudoresponse regulator protein 37 (PRR37) controls photoperiodic flowering in sorghum. *Proc Natl Acad Sci USA.* 108(39):16469–16474. doi:[10.1073/pnas.1106212108](https://doi.org/10.1073/pnas.1106212108).
- Murphy RL, Morishige DT, Brady JA, Rooney WL, Yang S, Klein PE, Mullet JE. 2014. *Ghd7* (*Ma6*) represses sorghum flowering in long days: *Ghd7* alleles enhance biomass accumulation and grain production. *Plant Genome.* 7(2). doi:[10.3835/plantgenome2013.11.0040](https://doi.org/10.3835/plantgenome2013.11.0040).
- Myles S, Peiffer J, Brown PJ, Ersoz ES, Zhang Z, Costich DE, Buckler ES. 2009. Association mapping: critical considerations shift from

- genotyping to experimental design. *Plant Cell*. 21(8):2194–2202. doi:[10.1105/tpc.109.068437](https://doi.org/10.1105/tpc.109.068437).
- Nakamichi N. 2015. Adaptation to the local environment by modifications of the photoperiod response in crops. *Plant Cell Physiol*. 56(4):594–604. doi:[10.1093/pcp/pcu181](https://doi.org/10.1093/pcp/pcu181).
- Paccapelo MV, Kelly AM, Christopher JT, Verbyla AP. 2022. WGNAM: whole-genome nested association mapping. *Theor Appl Genet*. 135(7):2213–2232. doi:[10.1007/s00122-022-04107-x](https://doi.org/10.1007/s00122-022-04107-x).
- Paterson AH, Bowers JE, Bruggmann R, Dubchak I, Grimwood J, Gundlach H, Haberler G, Hellsten U, Mitros T, Poliakov A, et al. 2009. The Sorghum bicolor genome and the diversification of grasses. *Nature*. 457(7229):551–556. doi:[10.1038/nature07723](https://doi.org/10.1038/nature07723).
- Piepho H-P, Pillen K. 2004. Mixed modelling for QTLx environment interaction analysis. *Euphytica*. 137(1):147–153. doi:[10.1023/B:EUPH.0000040512.84025.16](https://doi.org/10.1023/B:EUPH.0000040512.84025.16).
- Rama Reddy NR, Ragimasalawada M, Sabbavarapu MM, Nadoor S, Patil JV. 2014. Detection and validation of stay-green QTL in post-rainy sorghum involving widely adapted cultivar, M35-1 and a popular stay-green genotype B35. *BMC Genomics*. 15(1):909. doi:[10.1186/1471-2164-15-909](https://doi.org/10.1186/1471-2164-15-909).
- Ratnadass A, Chantereau J, Coulibaly M, Cilas C. 2002. Inheritance of resistance to the panicle-feeding bug *eurystylus oldi* and the sorghum midge *stenodiplosis sorghicola* in sorghum. *Euphytica*. 123(1):131–138. doi:[10.1023/A:1014451103520](https://doi.org/10.1023/A:1014451103520).
- Reymond M, Muller B, Leonardi A, Charcosset A, Tardieu F. 2003. Combining quantitative trait loci analysis and an ecophysiological model to analyze the genetic variability of the responses of maize leaf growth to temperature and water deficit. *Plant Physiol*. 131(2):664–675. doi:[10.1104/pp.013839](https://doi.org/10.1104/pp.013839).
- Rodríguez-Álvarez MX, Boer MP, van Eeuwijk FA, Eilers PH. 2018. Correcting for spatial heterogeneity in plant breeding experiments with P-splines. *Spat Stat*. 23:52–71. doi:[10.1016/j.spasta.2017.10.003](https://doi.org/10.1016/j.spasta.2017.10.003).
- Rooney WL, Aydin S. 1999. Genetic control of a photoperiod-sensitive response in Sorghum bicolor (L.) Moench. *Crop Sci*. 39(2):397–400. doi:[10.2135/cropsci1999.0011183X0039000200016x](https://doi.org/10.2135/cropsci1999.0011183X0039000200016x).
- Sagnard F, Deu M, Dembélé D, Leblois R, Touré L, Diakité M, Calatalyud C, Vaksman M, Bouchet S, Malle Y, et al. 2011. Genetic diversity, structure, gene flow and evolutionary relationships within the Sorghum bicolor wild-weedy-crop complex in a western African region. *Theor Appl Genet*. 123(7):1231–1246. doi:[10.1007/s00122-011-1662-0](https://doi.org/10.1007/s00122-011-1662-0).
- Scott MF, Ladejobi O, Amer S, Bentley AR, Biernaskie J, Boden SA, Clark M, Dell'Acqua M, Dixon LE, Filippi CV, et al. 2020. Multi-parent populations in crops: a toolbox integrating genomics and genetic mapping with breeding. *Heredity (Edinb)*. 125(6):396–416. doi:[10.1038/s41437-020-0336-6](https://doi.org/10.1038/s41437-020-0336-6).
- Soumaré M, Kouressy M, Vaksman M, Maikano I, Bazile D, Traoré PS, Traoré S, Dingkuhn M, Touré A, Vom Brocke K. 2008. Prévision de l'aire de diffusion des sorghos photopériodiques en Afrique de l'Ouest. *Cah Agric*. 17(2):160–164. doi:[10.1684/agr.2008.0183](https://doi.org/10.1684/agr.2008.0183).
- Sparks AH. 2018. Nasapower: a NASA POWER global meteorology, surface solar energy and climatology data client for R. *J Open Source Software*. 3(30):1035. doi:[10.21105/joss.01035](https://doi.org/10.21105/joss.01035).
- Takai T, Yonemaru J, Kaidai H, Kasuga S. 2012. Quantitative trait locus analysis for days-to-heading and morphological traits in an RIL population derived from an extremely late flowering F₁ hybrid of sorghum. *Euphytica*. 187:411–420. doi:[10.1007/s10681-012-0727-8](https://doi.org/10.1007/s10681-012-0727-8).
- Tardieu F. 2003. Virtual plants: modelling as a tool for the genomics of tolerance to water deficit. *Trends Plant Sci*. 8(1):9–14. doi:[10.1016/S1360-1385\(02\)00008-0](https://doi.org/10.1016/S1360-1385(02)00008-0).
- Thera K. 2017. Analyse des déterminants génétiques contrôlant la production et la composition de la tige chez le sorgho (*Sorghum bicolor* [L.] Moench). Intégration des approches bi-et multi-parentales. Thèse de doctorat: Sciences agronomiques et écologie. Montpellier: Montpellier SupAgro.
- van Eeuwijk FA, Bink MC, Chenu K, Chapman SC. 2010. Detection and use of QTL for complex traits in multiple environments. *Curr Opin Plant Biol*. 13(2):193–205. doi:[10.1016/j.pbi.2010.01.001](https://doi.org/10.1016/j.pbi.2010.01.001).
- Van Oosterom E, Carberry P, Hargreaves J, O'leary G. 2001. Simulating growth, development, and yield of tillering pearl millet: II. Simulation of canopy development. *Field Crops Res*. 72(1):67–91. doi:[10.1016/S0378-4290\(01\)00165-4](https://doi.org/10.1016/S0378-4290(01)00165-4).
- Verbeke G, Molenberghs G, Verbeke G. 1997. Linear Mixed Models for Longitudinal Data. New York (NY): Springer.
- Verbyla AP, Cavanagh CR, Verbyla KL. 2014. Whole-Genome analysis of multi-environment or multitrait QTL in MAGIC. G3 (Bethesda). 4(9):1569–1584. doi:[10.1534/g3.114.012971](https://doi.org/10.1534/g3.114.012971).
- Vom Brocke K, Trouche G, Weltzien E, Kondombo-Barro CP, Sidibé A, Zougmore R, Gozé E. 2014. Helping farmers adapt to climate and cropping system change through increased access to sorghum genetic resources adapted to prevalent sorghum cropping systems in Burkina Faso. *Exp Agric*. 50(2):284–305. doi:[10.1017/S0014479713000616](https://doi.org/10.1017/S0014479713000616).
- VSN International. 2022. Genstat for Windows 22nd Edition. Hemel Hempstead, UK: VSN International.
- Wei J, Xu S. 2016. A random-model approach to QTL mapping in multiparent advanced generation intercross (MAGIC) populations. *Genetics*. 202(2):471–486. doi:[10.1534/genetics.115.179945](https://doi.org/10.1534/genetics.115.179945).
- Wolabu TW, Tadege M. 2016. Photoperiod response and floral transition in sorghum. *Plant Signal Behav*. 11(12):e1261232. doi:[10.1080/15592324.2016.1261232](https://doi.org/10.1080/15592324.2016.1261232).
- Wu X-L, Jannink J-L. 2004. Optimal sampling of a population to determine QTL location, variance, and allelic number. *Theor Appl Genet*. 108(7):1434–1442. doi:[10.1007/s00122-003-1569-5](https://doi.org/10.1007/s00122-003-1569-5).
- Xavier A, Xu S, Muir WM, Rainey KM. 2015. NAM: association studies in multiple populations. *Bioinformatics*. 31(23):3862–3864. doi:[10.1093/bioinformatics/btv448](https://doi.org/10.1093/bioinformatics/btv448).
- Xu S. 1998. Mapping quantitative trait loci using multiple families of line crosses. *Genetics*. 148(1):517–524. doi:[10.1093/genetics/148.1.517](https://doi.org/10.1093/genetics/148.1.517).
- Xu Y. 2016. Envirotyping for deciphering environmental impacts on crop plants. *Theor Appl Genet*. 129(4):653–673. doi:[10.1007/s00122-016-2691-5](https://doi.org/10.1007/s00122-016-2691-5).
- Yang S, Murphy RL, Morishige DT, Klein PE, Rooney WL, Mullet JE. 2014. Sorghum phytochrome B inhibits flowering in long days by activating expression of SbPRR37 and SbGHD7, repressors of SbEHD1, SbCN8 and SbCN12. *PLoS One*. 9(8):e105352. doi:[10.1371/journal.pone.0105352](https://doi.org/10.1371/journal.pone.0105352).
- Yu J, Holland JB, McMullen MD, Buckler ES. 2008. Genetic design and statistical power of nested association mapping in maize. *Genetics*. 178(1):539–551. doi:[10.1534/genetics.107.074245](https://doi.org/10.1534/genetics.107.074245).
- Zhang Z, Wang W, Valdar W. 2014. Bayesian modeling of haplotype effects in multiparent populations. *Genetics*. 198(1):139–156. doi:[10.1534/genetics.114.166249](https://doi.org/10.1534/genetics.114.166249).
- Zhang J, Zhang D, Fan Y, Li C, Xu P, Li W, Sun Q, Huang X, Zhang C, Wu L, et al. 2021. The identification of grain size genes by RapMap reveals directional selection during rice domestication. *Nat Commun*. 12:5673. doi:[10.1038/s41467-021-25961-1](https://doi.org/10.1038/s41467-021-25961-1).
- Zheng C, Boer MP, van Eeuwijk FA. 2015. Reconstruction of genome ancestry blocks in multiparental populations. *Genetics*. 200(4):1073–1087. doi:[10.1534/genetics.115.177873](https://doi.org/10.1534/genetics.115.177873).