

Genetic dissection of epistatic and QTL by environment interaction effects in three bread wheat genetic backgrounds for yield-related traits under saline conditions

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Abstract Salt stress represents a major impediment to global wheat production. Development of wheat varieties that offer tolerance to salt stress would increase productivity. Here we report on the results of a genetic study of salt tolerance in bread wheat across multiple genetic backgrounds and environments, with the goal of identifying quantitative trait loci (QTLs) for 9 yield-related traits that are both genetic background independent and environmentally stable. Three RIL populations derived from crosses between a super salt tolerant landrace (Roshan) and 3 breadwheat cultivars (Falat, Sabalan, Superhead#2) that

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vary in salt tolerance were phenotyped in three environments. Genetic maps were constructed for each RIL population and independent analyses of each population/environment combination revealed significant associations of 92 genomic regions with the traits evaluated. Joint analyses of yield-related traits across all populations revealed a strong genetic background effect, with no QTLs shared across all genetic backgrounds. Fifty-seven QTLs identified in the independent analysis co-localized with those in the joint analysis. Overall, only 3 QTLs displayed significant epistatic interactions. Additionally, a total of 67 QTLs were identified in QTL analysis across environments, two of these (QSPL.3A, QBYI.7B-1) were both stable and not reported previously. Such novel and stable QTLs may accelerate marker-assisted breeding of new highly productive and salt tolerant bread-wheat varieties.

Keywords Bread wheat · Epistatic effect · Genetic background - QTL by environment effect - QTL mapping - Salt stress

Introduction

Bread wheat *(Triticum aestivum)* is a globally important crop, providing approximately 30% of global grain production, and 20% of total calories and plant-derived protein for the world's population (FAO [2018](#page-23-0)). To meet expected food requirements of wheat-consuming countries over the next half century, it is estimated that wheat production must increase by approximately 70% (Ray et al. [2012\)](#page-24-0). According to the FAO, salinity stress is a major constraint to agricultural food production generally and to wheat specifically. Salinity stress reduces yields and limits the use of agricultural land. Given that around 20% of all agricultural land is salinated, the development of salt tolerant crop varieties would contribute importantly to food security.

Salinity can have several different negative effects on plant growth and reproduction, including reductions in water availability, ion toxicity, and induction of nutrient deficiencies. As a consequence, plant responses to salinity stress are typically genetically and physiologically complex, involving the interaction of many gene pathways, as well as the environment (Flowers and Flowers [2005\)](#page-23-0). Hence, not only is the identification and molecular characterization of salinity stress related quantitative trait loci (QTLs) critical for accelerating marker-aided breeding of salt tolerant crops, but also such QTL analyses are most likely to be successful if conducted under multiple environments with the varying degrees of stress (Mathews et al. [2008](#page-23-0)).

Multi-environment trials (METs) are often used to evaluate the performance of genotypes across sites and years. If the interest is exclusively in phenotypic variation, then a panel that maximizes crop diversity is typically employed. However, if genetic information is wanted as well, then METs for bi-parental populations are routinely examined, since they enable detection of QTLs and their interactions with each other and the environment. Examples include a recent study of 150 recombinant inbred lines (RILs) of maize to evaluate three ear-leaves area across multi-environments via inclusive composite interval mapping (Cui et al. [2017](#page-23-0)). Similarly, a doubled haploid population of 222 lines was characterized with 182 markers and grown in multi-environments to dissect QTL by environment interactions for grain yield components in winter wheat (Zheng et al. [2010](#page-24-0)). With sufficient marker density, one can conduct genetic analyses in more complex populations for genetic analyses, such as NAM or MAGIC populations, or diversity panels. Such association mapping population approaches have the advantage of sampling many more alleles underlying traits of interest, but are less powerful for assessing interactions among alleles at within or among loci.

Interactions between non-allelic genes (epistasis) have become an increasingly important focus of QTL studies since epistatic interactions appear to especially frequent for performance related traits such as plant height and yield. For example, Zhang et al. ([2008\)](#page-24-0) conducted a series of trials in which they found a significant epistatic effect for plant height in a population of doubled haploid wheat. Epistatic interactions can be important for morphological and developmental traits as well, such as kernel morphometric traits (Prashant et al. [2012](#page-23-0)) and coleoptile growth in wheat (Rebetzke et al. [2007](#page-24-0)).

Another major difficulty of marker-assisted breeding projects is the genetic background (GB) effect. GB impedes general utilization of QTLs identified in different backgrounds. Several studies have revealed that GB acts on the expression of QTL for yield and its components (Yao et al. [2016](#page-24-0); Venuprasad et al. [2012;](#page-24-0) Prashant et al. [2012;](#page-23-0) Wei et al. [2009;](#page-24-0) Han et al. [2012;](#page-23-0)Wang et al. [2014;](#page-24-0) Vikram et al. [2011](#page-24-0)).

Whereas some research has been carried out on wheat QTL mapping for salinity stress, there have been few empirical investigations into main, epistatic, environment and genetic background effects in one comprehensive experiment. In this study, three RIL populations with diverse salinity tolerance and genetic backgrounds (Roshan \times Falat, Roshan \times Sabalan and Roshan \times Superhead#2) were used to discover genomic regions underlying phenotypic variation in yield-related traits under salinity stress. The three RIL populations were evaluated across distinct environments that varied in salinity stress. The major objectives of this study were to (1) detect QTLs for morphological traits and grain yield-related traits under salinity stress in each genetic background and environment; (2) evaluate whether GB affects the identification and expression of QTLs; (3) investigate epistatic effects among detected QTLs; and (4) examine QTL by environment effects and find the most stable QTLs across different environments.

Materials and methods

Plant materials and DNA extraction

Three RIL mapping populations were derived from crosses between a common parent, Roshan (tolerant to salinity stress, tall, landrace) and three different parents: (1) Falat (highly sensitive to salinity stress, high grain yield, dwarf, cultivar); (2) Sabalan (sensitive to salinity stress, high grain yield, tall, cultivar); and (3) Superhead#2 (highly sensitive to salinity stress, high grain yield, dwarf, cultivar). The common parent Roshan has been reported as a salt tolerant landrace in several salinity stress experiments (Poustini and Siosemardeh [2004;](#page-23-0) Dehdari et al. [2005](#page-23-0)). All the crosses were carried out in 2003. Roshan*Falat (RF), Roshan*Sabalan (RS) and Roshan*Superhead#2 (RSH) RIL populations contain 313, 254 and 186 genotypes, respectively. They were developed by single seed descent at the Agricultural Biotechnology Research Institute of Iran in 2010 (ABRII, Karaj, Iran) (Supplementary Figure 1). 100 mg leaf tissue of each RIL was collected from seedlings for extraction of high-quality genomic DNA following the Triticarte plant DNA extraction protocol ([http://www.triticarte.](http://www.triticarte.com.au/content/DNA-preparation.html) [com.au/content/DNA-preparation.html\)](http://www.triticarte.com.au/content/DNA-preparation.html). Extracted DNA was adjusted to a concentration of 50 ng/ μ l for marker analysis.

Genetic linkage map

Genomic DNA of RF, RS and RSH RIL populations were subjected to Diversity Arrays Technology (DArT) genome profiling (Akbari et al. [2006](#page-22-0); Wenzl et al. [2004\)](#page-24-0) at Triticarte Pty Ltd, Australia [\(http://](http://www.triticarte.com.au) [www.triticarte.com.au\)](http://www.triticarte.com.au) (raw data is available in Supplementary Data). DArT generates whole-genome fingerprints in a single microarray-based assay by scoring the presence versus absence of DNA fragments in genomic representations generated from samples of genomic DNA (Akbari et al. [2006\)](#page-22-0). Polymorphic markers were used to construct the linkage map using QTL IciMapping software version 4.1 [\(http://www.isbreeding.net\)](http://www.isbreeding.net) and the Kosambi mapping function (Kosambi [1943](#page-23-0)). Heterozygous loci were considered as missing data and the threshold for the likelihood of odds (LOD) ratio was set to 3.0.

Field trials and trait evaluation

The 313, 254 and 186 genotypes within each RIL population were evaluated in three different environments; Kerman in 2012, Kerman in 2013 (30 \degree 20' N and $56^{\circ}54'$ E) and Yazd in 2011 (32°30' N and $54^{\circ}05'$ E), all of which were sufficiently saline (electrical conductivity values of > 4 dS m⁻¹) to produce

deleterious effects on wheat (McFarland et al. [2014](#page-23-0)). Field experiments were carried out in homogenized salinity plots at CEAS (Center of Excellence for Abiotic stresses in Cereals). Electrical conductivity (EC) values in the Kerman experimental field were 12.5 and 10 dS m^{-1} for soil and for irrigation water, respectively. Similarly, EC values of 10.5 and 9 dS m^{-1} were recorded for soil and for irrigation water, respectively, in Yazd. RF, RS and RSH in Kerman-2013 and RF, RS in Kerman-2012 were seeded in an incomplete block design (lattice) with two replications while all three RIL populations in Yazd-2011 experiment and RSH in Kerman-2012 experiment were laid out with an augmented design. In the augmented design, sets of 20 lines were assigned randomly to a block with 3 check cultivars (Arg, Bam, Kavir). Field trial characteristics and traits evaluated are highlighted in Table [1](#page-3-0). In all experiments, plots were 200 cm long and six rows wide, with 20 cm spaces between rows and 10 cm between two plants in a row. The experiments were carried out during the local wheat-growing season (November–May). Weather data was collected from the nearest weather station for each experiment and summarized in Supplementary Figure 2. Standard agronomic practices were carried out to minimize weed and insect damage in order to reach maximum grain yield. The 4 center rows of each plot were used to collect data for plant height (PHT, measured from the soil surface to the tip of the tallest spike), spike length (SPL), spike weight (SPW), spikes per plant (SPP), weight of kernels per plant (WKP), thousand kernel weight (TKW, kernel weight was measured based on 100 kernels and converted to 1000-kernal weight), biological yield per m^2 (BYI), grain yield per m^2 (GYLD, determined as the average weight of bulked harvested grain per square meter) and harvest index (HAI) (Grain weight/Total biomass) in the RF population. In the RS population PHT, SPL, SPW, TKW, BYI, GYLD and HAI were measured. Lastly, in the RSH population PHT, SPL, TKW and GYLD were evaluated. Five randomly chosen plants from 4 central rows of each plot were phenotyped for PHT, SPL, SPW, SPP, WKP and TWK. The values were averaged and used as the measurements for the plot. BYI, GYLD and HAI were evaluated based on one central square meter. Experimental error was calculated based on the replicated checks in the augmented design and used to calculate adjusted genotype means for blocks.

However, the PROC LATTICE procedure in SAS (SAS Institute, version 9.1.3) was used to calculate adjusted means for lattice design experiments. Adjusted values of each trait were used for QTL mapping, except that square root normalizing transformations were performed on GYLD (in RF, RS and RSH), BYI (in RF and RS) and SPL (in RF and RSH).

QTL mapping

Main additive QTLs (M-QTLs) in each environment and genetic background were identified by the method of inclusive composite interval mapping (ICIM) by QTL IciMapping version 4.1 (Li et al. [2008](#page-23-0)). Scanning step and the $PIN (P)$ value for entering variables) values were set at 5 and 0.01, respectively. Chromosomal regions with $LOD \geq 3.0$ were considered as significant M-QTLs.

ICIM epistatic interaction analysis was used to find possible epistatic interactions among detected M-QTLs. Genomic regions with LOD value ≥ 5.0 were declared as significant epistatic QTLs (E-QTLs).

The multi-environment trials (MET) function in QTL IciMapping version 4.1 was employed to detect QTL by environment interactions across all environments in each genetic background. QTLs with LOD scores ≥ 3.0 were selected for QTL stability analysis.

All QTLs were labeled in a precise fashion. The QTL identification labels break down as follows: An uppercase 'Q' signifies 'QTL'; the letters following the Q and prior to the period are an abbreviation of a specific corresponding trait; followed by the wheat chromosome of the corresponding QTL. Lastly, QTLs that have more than one locus in the same chromosome are defined by a numerical value that is further separated by a dash. M-QTLs and QTLs that were detected in multi-environment trials were labeled separately.

To clarify the pattern of QTL stability, a biplot methodology was used. PCA was performed on QTL by environment interaction effects. The first principal component score (absolute value) for each QTL was plotted against its absolute additive effect value. QTLs with absolute additive effects greater than the additive by environment effects are considered stable QTLs (Li et al. [2015](#page-23-0)).

Results

Evaluation of phenotypic traits revealed a wide range of phenotypic variation. Significant differences were observed among RILs for most of the traits in each environment (data not shown). Descriptive statistics (maximum, minimum, standard deviation and mean value) of evaluated traits for different populations and environments are presented in Table [2](#page-5-0). For example, the lowest grain yield was 2.72 g/m^2 and the highest was 664 g/m^2 in RF Kerman-2013 and RSH Kerman-2012, respectively. In addition, the shortest genotype was found in RS Kerman-2012 (15.41 cm) and the tallest in RSH Kerman-2012 (94.5 cm). Furthermore, spike length of the RF population ranged from 4.8 to 11.1 cm in Kerman-2013, while RSH population spike length ranged from 3.6 to 27 cm in Kerman-2012. In the majority of environments, the maximum values of each trait were vastly larger than the minimum values. All evaluated traits displayed continuous phenotypic variation in all environments, consistent with polygenic inheritance (Supplementary Figure 3).

Construction of linkage maps

RF, RS, RSH populations were genotyped with 2605, 2717 and 868 DArT markers, respectively. Linkage analysis was carried out after excluding redundant or monomorphic markers from the data set. DArT markers were genetically mapped to 21 linkage groups based on anchor information received from Triticarte [\(http://www.diversityarrays.com](http://www.diversityarrays.com)) and linkage analysis at LOD 3.0. In the RF population, a total of 810 polymorphic markers, spanning a total length of 6095.88 cM with an average density of one marker per 7.52 cM, were mapped. In the RS population, the total map length was 5545.98 cM and the average interval between loci was 15.41 cM. There were 486 markers assigned to 21 chromosomes with an average of 23 markers per chromosome. Chromosome 7D in the RS population was excluded from QTL mapping analysis since only one single marker was mapped to this chromosome. The linkage map for the RSH population consisted of 660 markers and spanned 5905.53 cM, with an average marker density of 10.89 cM. Additional information about the linkage maps is in Table [3.](#page-6-0)

QTL analysis

A total of 92 putative M-QTLs were identified across the 9 experiments (Table [4\)](#page-7-0). Analyses of epistatic interactions among the M-QTLs, revealed, 3 E-QTLs (Table [5](#page-10-0)). Additionally, QTL by environment analyses detected a total of 67 intervals with significant additive main effects and/or additive by environment effects across multiple environments (Table [6](#page-11-0) and Fig. [1\)](#page-14-0). Of these, 49 intervals co-localized with M-QTLs whereas the remaining 18 intervals did not have a significant main effect in any of the 9 experiments (Table [6](#page-11-0)). Six of the 18 intervals had stable effects across different environments (Fig. [2](#page-15-0)). In the joint analysis, 57 QTLs were compared across the 3 mapping populations. All 57 QTLs were previously detected in the independent analysis, and 29 QTLs were in common between the joint and QTL by environment analyses.

The QTL analyses in single and multi-environments, epistatic interactions and genetic background are described in more detail in the following sections: joint analysis and independent analysis. The joint analysis section compares QTLs for common traits across the 3 mapping populations and the independent analysis section provides QTL information for individual mapping populations across environments.

Joint analysis

A total of 16 distinct M-QTLs for GYLD were detected across the 3 mapping populations (Table [7](#page-16-0)). Among these M-QTLs, 9 (56.25%) were identified in the RF population, while $3(18.75%)$ and $4(25%)$ were detected in the RS and RSH populations, respectively. These M-QTLs individually accounted for between 45.13% (RS population in Kerman 2012) and 2.60% (RF population in Kerman 2012) of GYLD variation. In the RF population, the positive alleles for 6 M-QTLs were derived from Roshan. In contrast, Roshan contributed only a single positive allele to RS and RSH M-QTLs. No common M-QTLs were identified across the 3 mapping populations. However, 3, 1 and 3 M-QTLs were detected across multiple environments in RF, RS and RSH, respectively via QTL by environment analysis. The other 9 M-QTLs were environment specific. Two M-QTLs (QGYLD.6A and QGYLD.3B) in RSH and a single M-QTL (QGYLD.1A) in RS displayed stable effects across

2013, KR12 Kerman-2012, Y11 Yazd-2011

Table 3 Characteristics of the genetic maps employed in this study

Chr. ^a	Roshan *Falat						Roshan*Sabalan					Roshan*Superhead#2				
	N^b	Length ^c	$\mathbf{Max}^{\mathbf{d}}$	Min^e	Avef	\mathbf{N}^{b}	$\mathrm{Length}^\mathrm{c}$	$\mathbf{Max}^{\mathbf{d}}$	Min ^e	Avef	\mathbf{N}^{b}	Length ^c	$\mathbf{Max}^{\mathbf{d}}$	Min^e	Avef	
1A	31	340.73	73.96	0.0	11.4	46	438.51	107.94	0.0	9.7	44	407.69	77.56	0.0	9.5	
2A	32	345.49	49.75	0.0	11.1	10	160.22	41.73	0.0	17.8	29	396.97	59.65	0.0	14.2	
3A	39	260.19	35.56	0.0	6.9	14	331.89	74.69	0.0	25.5	22	264.91	67.03	0.0	12.6	
4A	32	181.22	63.72	0.0	5.9	35	338.88	62.24	0.0	10.0	36	181.63	57.29	0.0	5.2	
5A	12	213.41	92.31	0.2	19.4	34	397.96	55.16	0.0	12.1	33	406.34	61.21	0.0	12.7	
6A	38	249.03	74.35	0.0	6.7	5	191.25	119.47	0.2	47.8	28	383.84	60.84	0.0	14.2	
7A	51	400.90	81.64	0.0	8.0	39	162.78	55.40	0.0	4.3	39	402.74	81.13	0.0	10.6	
1B	85	293.29	27.47	0.0	3.5	29	288.12	74.04	0.0	10.3	26	370.13	93.74	0.0	14.8	
2B	62	529.65	45.25	0.0	8.7	25	253.29	40.88	0.0	10.6	32	284.27	84.18	0.0	9.2	
3B	125	684.72	69.14	0.0	5.5	52	364.42	53.08	0.0	7.2	44	462.86	53.73	0.0	10.8	
4B	25	277.13	59.60	0.0	11.6	13	156.82	51.72	0.0	13.1	12	276.45	78.07	0.0	25.1	
5B	30	383.95	68.07	0.0	13.2	27	164.99	43.15	0.0	6.4	8	70.54	69.31	0.0	10.1	
6B	53	478.66	42.62	0.0	9.2	16	430.87	100.64	0.0	28.7	15	134.43	70.53	0.0	9.6	
7B	44	343.32	43.77	0.0	8.0	$\overline{2}$	0.21	0.21	0.2	0.2	130	164.14	39.61	0.0	1.3	
1D	47	133.08	18.28	0.0	2.9	15	192.12	83.08	0.0	13.7	25	168.26	30.48	0.0	7.0	
2D	30	341.75	142.00	0.0	11.8	12	189.50	107.94	0.0	17.2	33	371.74	84.47	0.0	11.6	
3D	23	226.56	75.18	0.0	10.3	31	332.24	100.19	0.0	11.1	18	227.08	54.34	0.0	13.4	
4D	3	15.78	15.24	0.5	7.9	10	345.45	107.03	0.2	38.4	10	95.48	30.33	2.7	10.6	
5D	8	80.04	27.80	0.3	11.4	41	419.46	64.40	0.0	10.5	40	356.25	52.27	0.0	9.1	
6D	10	226.94	78.56	0.2	25.2	29	387.00	115.13	0.0	13.8	34	477.05	59.95	0.0	14.5	
7D	30	90.04	16.97	0.0	3.1	1			$\qquad \qquad -$	$\overline{}$	2	2.73	2.73	2.7	2.7	
Total	810	6095.88	142.00	0.0	7.7	486	5545.98	119.47	0.0	11.9	660	5905.53	93.74	0.0	9.2	
A	235	1990.97	92.31	0.0	7.3	183	2021.49	119.47	0.0	11.3	231	2444.12	81.13	0.0	11.3	
B	424	2990.72	69.14	0.0	7.2	164	1658.72	100.64	0.0	10.6	267	1762.82	93.74	0.0	9.8	
D	151	1114.19	142.00	0.0	7.7	139	1865.77	115.13	0.0	14.1	162	1698.59	84.47	0.0	11.0	

a Chromosome

^bNumber of DArT markers

^cLength of map

^dMaximum interval

e Minimum interval

f Average interval

environments (Fig. [2\)](#page-15-0). No epistatic interactions were identified for M-QTLs associated with GYLD.

For PHT, 11 and 7 M-QTLs were discovered in the RF and RSH populations, respectively, whereas only a single M-QTL was detected in the RS population (Table [7](#page-16-0)). Two of the M-QTLs (QPHT.6D-2, QPHT.7A-3) in RSH explained greater than 20% of phenotypic variance (i.e., major QTLs). In contrast, none of the 12 M-QTLs in the RS and RF populations had a major effect. Roshan alleles increased PHT by an average of 2.78 cm (ranging from 2.34 to 3.10 cm) in RSH, but only by 0.91 and 1.83 cm in RS and RF, respectively. A comparison of the 9 experiments revealed that QPHT.7A-2 and QPHT.7A-3 are probably the same QTL across two different genetic backgrounds (RF and RSH) in the same environment (Kerman-2013). In addition, 11 M-QTLs have significant QTL by environment effects. Conversely, the

Table 4 Independent analysis, genomic regions associated with yield-related and morphological traits in different genetic backgrounds and environments

Trait	QTL	Pop ^a	$\mathrm{ENV}^{\mathrm{b}}$	Chr.	Pos.	Marker interval	LOD	PVE^{c} $(\%)$	$\mathbf{Add}^\mathbf{d}$	$+A$ llele e ^e
BYI	QBYI.2A-1	RF	Kr13	2A	90	wPt-7721-wPt-7187	3.3039	3.4964	0.5605	Roshan
	OBYI.2A-2		Kr12	2A	95	wPt-7187-wPt-115	3.2618	3.4926	1.2366	Roshan
	QBYI.7A	RF	Y11	7A	225	wPt-4960-wPt-3523	4.7094	7.0759	0.8213	Roshan
	QBYI.7B-1		Kr13	7B	155	wPt-6484-wPt-6657	5.9391	7.4994	0.8059	Roshan
	QBYI.7B-2	RF	Kr13	7B	330	wPt-4230-wPt-8283		3.7623	0.5690	Roshan
	QBYI.4D	RS	Kr13	4D	345	wPt-8794-wPt-733910	3.0688	3.8256	-0.5090	Sabalan
GYLD	QGYLD.1B	RF	Kr12	1B	180	wPt-320-wPt-6434	3.5866	3.4222	0.7028	Roshan
	QGYLD.2A-1	RF	Kr12	2A	95	wPt-7187-wPt-115	3.0578	2.8703	0.4360	Roshan
	QGYLD.2A-2	RF	Y11	2A	320	wPt-6687-wPt-729945	3.3546	7.9449	-0.6110	Falat
	QGYLD.2B	RF	Kr13	2B	300	wPt-6932-wPt-4301	3.4948	4.2513	0.4721	Roshan
	QGYLD.3D	RF	Kr13	3D	50	wPt-7241-wPt-730935	3.1998	3.6667	-0.4490	Falat
	QGYLD.4D-1	RF	Kr12	4D	$\boldsymbol{0}$	wPt-3058-wPt-672143	3.0529	2.6050	0.4492	Roshan
	QGYLD.6A-2	RF	Kr12	6A	160	wPt-228-wPt-741630	3.6348	4.5674	-0.6482	Falat
	QGYLD.7A	RF	Y11	7A	225	wPt-4960-wPt-3523	3.9589	5.2413	0.5157	Roshan
	QGYLD.7B	RF	Kr13	7B	155	wPt-6484-wPt-6657	4.6688	5.4045	0.5331	Roshan
	QGYLD.6A-1	RS	Kr13	6A	20	wPt-9589-wPt-653	3.9476	15.1472	-1.0562	Sabalan
	QGYLD.1A	RS	Y11	1A	110	wPt-664968-wPt-5316	3.4660	4.7872	0.3450	Roshan
	QGYLD.6B	RS	Kr12	6 _B	95	wPt-494-wPt-741686	3.0253	45.1356	2.4571	Roshan
	QGYLD.6A-3	RSH	Kr13	6A	380	wPt-5037-wPt-669672	3.7796	5.3191	0.6092	Roshan
	QGYLD.1D	RSH	Y11	1D	$\mathbf{0}$	wPt-731338-wPt-667083	3.3204	5.4482	-0.5941	Superhead#2
	QGYLD.3B	RSH	Kr13	3B	160	wPt-731378-wPt-2559	3.8335	6.5998	-0.6797	Superhead#2
	QGYLD.4D-2	RSH	Kr13	4D	20	wPt-7769-wPt-665622	3.1595	4.4888	-0.5595	Superhead#2
HAI	QHAI.4D-1	RF	Y11	4D	5	wPt-3058-wPt-4572	3.0969	5.6897	0.0124	Roshan
	QHAI.5A-2	RF	Kr12	5A	185	wPt-4249-wPt-3334	5.8609	19.6774	-0.0274	Falat
	QHAI.2A	RF	Kr13	2A	120	wPt-664128-wPt-1114	3.3323	3.3960	0.0140	Roshan
	QHAI.2B	RF	Kr12	2B	290	wPt-3561-wPt-4997	4.6507	5.6591	0.0141	Roshan
	QHAI.3B-1	RF	Kr12	3B	360	wPt-4220-wPt-669517	5.3456	8.2628	-0.0178	Falat
	QHAI.3B-2	RF	Kr13	3B	480	wPt-8781-wPt-10948	3.7460	3.8287	0.0132	Roshan
	QHAI.6D-1	RF	Kr13	6D	95	wPt-729831-wPt-5331	3.1923	3.2437	-0.0122	Falat
	QHAI.4D-2	RS	Y11	4D	275	wPt-3563-wPt-8794	3.1755	5.9101	0.0110	Roshan
	QHAI.5A-1	RS	Kr12	5A	55	tPt-8942-wPt-1505	3.5624	20.0412	-0.0100	Sabalan
	QHAI.1B	RS	Kr12	1B	55	wPt-734314-wPt-7259	5.4342	41.9097	-0.0143	Sabalan
	QHAI.5B	RS	Kr13	5B	130	wPt-731592-wPt-7809	3.7279	18.2084	-0.0543	Sabalan
	QHAI.6A	RS	Kr13	6A	15	wPt-9589-wPt-653	3.8039	13.5752	-0.0338	Sabalan
	QHAI.6D-2	RS	Kr12	6D	130	wPt-3873-wPt-8007	4.2693	9.0634	0.0089	Roshan

Table 4 continued

Table 4 continued

Min. minimum, Max. maximum, SD standard deviation, PHT plant height, SPL spike length, SPW spike weight, WKP weight of kernels in plant, TKW thousand kernel weight, SPP spike per plant, GYLD grain yield per m^2 , BYI biological yield per m^2 , HAi harvest index, RF Roshan*Falat, RS Roshan*Sabalan, RSH Roshan*Superhead#2, KR13 Kerman-2013, KR12 Kerman-2012, Y11 Yazd-2011

^aMapping population for detected QTL

^bThe environment of detected QTL

c Phenotypic variation explained

^dAdditive effect of detected QTL

e Source of positive allele

other 8 M-QTLs had environment specific effects. Notably, strong evidence of stability across environments was found for 6 M-QTLs via biplot analysis (Fig. [2](#page-15-0)). No significant epistatic interactions were detected for M-QTLs underlying PHT.

Ten M-QTLs were discovered to be associated with SPL (Table [7](#page-16-0)). Of these, the majority (6) were identified in the RF population, whereas 3 M-QTLs were identified in RS and 1 in RSH. Of the 10 M-QTLs, one in each population had a major effect. Roshan contributed positive alleles to 3 M-QTLs in the RF population, 2 M-QTLs in the RS population and one in the RSH population. No common M-QTLs were found across the three mapping populations, although 4 M-QTLs had exhibited significant QTL by environment effects. Only one M-QTL (QSPL.3A) demonstrated environmental stability (Fig. [2\)](#page-15-0). No

epistatic interactions were observed among M-QTLs associated with SPL.

For TKW, 6, 5 and 1 M-QTLs were identified in the RF, RSH and RS populations, respectively (Table [7](#page-16-0)). Of these, only a single M-QTL (QTKW.5B) had a major effect in the RSH population at Kerman-2013. Analysis of epistatic interactions revealed a single significant interaction between QTKW.3B-2 and a locus on chromosome 3D (Table [5\)](#page-10-0). QTL by environment analysis revealed that environment had a significant effect on 4 M-QTLs in RSH, 3 in the RF, but none in RS. Only two M-QTLs (QTKW.7A-2 and QTKW.5B), both in the RSH population, were found to be environmentally stable (Fig. [2\)](#page-15-0).

Independent analysis

RF population

Fifty-seven M-QTLs were found to be associated with 9 traits in the RF population (Supplementary Figure 4). The majority of M-QTLs (26) were identified in the Kerman-2013 environment. In addition, 21 and 10 M-QTLs were discovered in Kerman-2012 and Yazd-2011, respectively (Supplementary Figure 5). The largest number of M-QTLs in this population were associated with PHT (11) followed by GYLD (9), HAI (7), TKW (6), SPL (6), WKP (6), SPW (5), BYI (5) and SPP (2). A single QTL (QSPL.4B) was detected that explained $> 20\%$ of the spike length variation. Epistatic interaction results indicated that an M-QTL associated with SPP on chromosome 5 (QSPP.5A) had epistatic interactions (Table 5). QTL by environment analysis detected 34 intervals, which co-localized with M-QTLs in RF. Of these, QPHT.6B-2, QBYI.7A, QBYI.7B-1 were found to be stable across environments (Fig. [2](#page-15-0)).

RS population

Of 18 M-QTLs detected for 7 traits in the RS population, 8 M-QTLs were identified in the Kerman-2013 environment, while 6 and 4 M-QTLs were discovered in Kerman-2012 and Yazd-2011, respectively (Supplementary Figure 5). QGYLD.6B and QHAI.1B were recognized as major QTLs. Four M-QTLs had significant effects in the QTL by environment analysis (Table [6\)](#page-11-0). Only QGYLD.1A was found to be stable across environments as shown by the biplot analysis (Fig. [2\)](#page-15-0). No evidence of significant epistatic interactions was found among M-QTLs in RS.

RSH population

Seventeen M-QTLs were found to be associated with 4 traits in the RSH population (Supplementary Figure 6). The largest number of M-QTLs (7) were identified for PHT, while the fewest M-QTLs (1) were associated with SPL. Five and 4 M-QTLs were found to be associated with TKW and GYLD, respectively. QSPL.3A, QTKW.5B, QPHT.6D-2 and QPHT.7A-3 represent major M-QTLs. Significant QTL by environment effects were found for 11 M-QTLs (Table [6](#page-11-0)).

aPhenotypic variation explained bAdditive effect of QTL

Phenotypic variation explained Additive effect of QTL

SPP spike per plant, GYLD grain yield per m², BYI biological yield per m², HAI harvest index, RF Roshan*Falat, RS Roshan*Sabalan, RSH Roshan*Superhead#2, KR13 Kerman-2012, YH Yazd-2011 SPP spike per plant, GYLD grain yield per m², BYI biological yield per m², HAI harvest index, RF Roshan*Falat, RS Roshan*Sabalan, RSH Roshan*Superhead#2, KR13 Kerman-2013, KR12 Kerman-2012, Y11 Yazd-2011

^aPhenotypic variation explained aPhenotypic variation explained

^bAdditive effect of detected QTL ^bAdditive effect of detected QTL

⁶Additive by Environment (Kerman-2013) effect cAdditive by Environment (Kerman-2013) effect

^dAdditive by Environment (Kerman-2012) effect d Additive by Environment (Kerman-2012) effect

^eAdditive by Environment (Yazd-2011) effect eAdditive by Environment (Yazd-2011) effect

'Co-localized M-QTLs fCo-localized M-QTLs

Table 6 continued

² Springer

Fig. 1 LOD profile of plant height (PHT), spike length (SPL), spike weight (SPW), weight of kernels in plant (WKP), thousand kernel weight (TKW), spikes per plant (SPP), grain yield per m²

Of these, QTKW.7A-2, QTKW.5B, QSPL.3A, QPHT.4B-1, QPHT.1D, QGYLD.6A and QGYLD.3B had stable effects across environments (Fig. [2](#page-15-0)). Significant epistatic interactions were only detected for QTKW.3B-2 (Table [5](#page-10-0)).

Discussion

The majority of wheat breeders have focused on enhancing drought tolerance, with relatively less effort directed towards salt tolerance (Munns et al. [2006](#page-23-0)). However, given the fairly large fraction of agricultural land affected by salt (Flowers and Yeo [1995\)](#page-23-0), and the extent of yield losses when growing wheat on such land (Sardouie-Nasab et al. [2013](#page-24-0)), a greater focus on the development of salt tolerant wheat varieties is increasingly critical. Fortunately, significant variation for salt tolerance can be found in the cultivar gene

(GYLD), biological yield per m^2 (BYI), harvest index (HAI) in different genetic backgrounds; Roshan*Falat (RF), Roshan*Sabalan (RS), Roshan*Superhead#2 (RSH) across environments

pool, so the development of such cultivars should be straightforward, although success (and speed) will depend on the genetic architecture and stability of traits associated with salt tolerance.

Genetic background

Recent advances in genomics and computational biology offer a means for dissecting the genetic architecture of complex traits such as salt tolerance. Furthermore, utilizing new genomic tools in markeraided breeding programs can accelerate identification and selection of desired genes compared to classical breeding (Hussain [2015;](#page-23-0) Saade et al. [2016;](#page-24-0) Budak et al. [2004](#page-22-0); Jahani et al. [2014;](#page-23-0) Castillo et al. [2008](#page-22-0)). However, the successful implementation of MAS requires that GB effects be understood. While numerous studies have demonstrated that GBs can influence QTL detection and estimation of effect sizes (Han

Fig. 2 Biplot analysis of QTL stability across environments, X: the first principal component scores (absolute value) of QTL by environment interaction effects, Y: main additive effect of QTLs (absolute value). QTLs under the thick line display larger QTL by environment interaction effects than main additive

et al. [2012](#page-23-0); Wei et al. [2009](#page-24-0); Yao et al. [2016](#page-24-0)), most studies still focus on QTLs underlying traits in a single population. The lack of repeatability of QTL effects across different genetic backgrounds (GB effect) and across environments (QEI effect) has limited the utilization of MAS in breeding (Price et al. [2002](#page-24-0); Courtois et al. [2003;](#page-22-0) Lafitte et al. [2004;](#page-23-0) Bernier et al.

effects, whereas QTLs above the line demonstrate larger main additive effects than QTL by environment interaction effects (stable QTL across environment). The dotted lines and red dots highlight different levels of QTL stability and stable QTLs, respectively. (Color figure online)

[2008\)](#page-22-0). Hence, the consistency of QTL effects in different GBs is a serious issue in marker-aided breeding projects.

Out of 92 reported M-QTLs in the present study by independent analyses of the three mapping populations across the three environments, only 2 (\sim 5%) M-QTLs were identified in 2 genetic backgrounds in

Table 7 continued

Table 7 continued

Table 7 continued

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Table 7 continued

Table 7 continued

Table 7 continued

 $\frac{1}{2}$ Min. minimum, Max. maximum, SD standard deviation, PHT plant height, SPL spike length, SPW spike weight, WKP weight of kernels in plant, TKW thousand kernel weight, SPP spike per plant, GYLD grain yield per m², BYI biological yield per m², HAI harvest index, RF Roshan*Falat, RS Roshan*Sabalan, RSH Roshan*Superhead#2, KR13 Kerman-Min. minimum, Max. maximum, SD standard deviation, PHT plant height, SPL spike length, SPW spike weight, WKP weight of kernels in plant, TKW thousand kernel weight, SPP spike per plant, GYLD grain yield per m², BYI biological yield per m², HAI harvest index, RF Roshan*Falat, RS Roshan*Sabalan, RSH Roshan*Superhead#2, KR13 Kerman-2013, KR12 Kerman-2012, Y11 Yazd-2011 2013, KR12 Kerman-2012, Y11 Yazd-2011

^aMapping population for detected QTL aMapping population for detected QTL

 $^{\rm b}$ The environment of detected QTL bThe environment of detected QTL

Phenotypic variation explained cPhenotypic variation explained

^dAdditive effect of detected QTL ^dAdditive effect of detected QTL

^eSource of positive allele eSource of positive allele

fAdditive by Environment (Kerman-2013) effect fAdditive by Environment (Kerman-2013) effect

⁸Additive by Environment (Kerman-2012) effect ^gAdditive by Environment (Kerman-2012) effect ^hAdditive by Environment (Yazd-2011) effect h Additive by Environment (Yazd-2011) effect

the same environment. Surprisingly, joint analyses failed to detect QTLs common to all 3 genetic backgrounds. This finding demonstrates the GBspecific effect of QTLs for yield-related traits under salinity stress. These findings are generally consistent with previous research. For example, Cui et al. ([2014\)](#page-23-0) reported that 7–36% of QTLs were shared across 2–3 wheat genetic backgrounds. Thus, it is clear that genetic background plays a large role in the expression of QTLs for salinity tolerance, and yield-related MAS for salt tolerance must take the genetic backgrounds of breeding populations into account.

Epistatic interactions

Fully understanding the impact of epistasis on quantitative traits remains a key challenge (Le Rouzic and Alvarez-Castro [2008\)](#page-23-0). In a detailed investigation into epistatic effects on wheat grain yield, Reif et al. ([2011\)](#page-24-0) concluded that exploitation of epistasis is key to increased selection gain via marker-assisted breeding. To elucidate the possible epistatic interaction effects of detected M-QTLs in the independent analysis, all possible effects were calculated based on 5 cM windows. A total of 191 epistatic interactions were found. Of these, only 3 co-localized with M-QTLs. The majority of the interacting loci have no significant main additive effects, similar to previous reports from wheat (Reif et al. [2011\)](#page-24-0), barley (Xu and Jia [2007](#page-24-0)), rice (Li et al. [1997\)](#page-23-0), humans (Nyholt et al. [2008](#page-23-0)), drosophila (Montooth et al. [2003](#page-23-0)) and mice (Leamy et al. [2005](#page-23-0)). Epistatic interactions involving the 3 M-QTLs alluded to above explained 25 to 37% of PVE. Interestingly, most of the epistatic interactions had a negative effect on traits, possibly implying that recombination in the mapping populations has disrupted favorable gene complexes.

QTL analysis in single and multi-environments

Previous studies of genetic responses to salt stress also indicate that the identification and expression of many QTLs is environment dependent. Environmental variation can result in changes in the magnitude and direction of QTL effects, leading to inconsistency in QTL detection, as well apparent reductions in LOD scores (Villalta et al. [2007](#page-24-0); Xue et al. [2009\)](#page-24-0). Inconsistency in QTL detection across multiple environments could be attributable to differing levels of stress experienced by the mapping population. Azadi et al. [\(2015](#page-22-0)) conducted research on QTL mapping of yield and yield components under normal and salt stress conditions in bread wheat. They recommended analyses of QTL by environment interactions as a means of accounting for inconsistent detection of QTLs between environments.

A better understanding of QTL by environment effects under salinity stress would lead to progress in wheat salinity tolerance breeding. Hence, QTL stability across multiple environments is key to developing a successful marker-aided breeding strategy. QTL mapping for yield-related traits across environments has previously been reported (Quarrie et al. [2006](#page-24-0); Zhang et al. [2010](#page-24-0); Azadi et al. [2015;](#page-22-0) Liu et al. [2014](#page-23-0); Guan et al. [2018](#page-23-0); Gao et al. [2015;](#page-23-0) Wu et al. [2015](#page-24-0); Würschum et al. [2015;](#page-24-0) Nadolska-Orczyk et al. [2017](#page-23-0); Shi et al. [2017\)](#page-24-0). In the present study, a total of 67 QTLs associated with yield-related and morphological traits were identified across multiple environments $(Table 6)$ $(Table 6)$ $(Table 6)$.

One of the most important morphological traits of wheat is plant height, since a significant gain in wheat yield occurred through the introduction of reduced height (Rht) dwarfing genes (Hedden [2003](#page-23-0); Zhang et al. [2006\)](#page-24-0). As shown in the biplots the 15 QTLs for plant height range from unstable to relatively stable across environments (Fig. [2](#page-15-0)). As shown in joint analyses QPHT.6A, QPHT.4B-1, QPHT.1D, QPHT.7A-1, QPHT.7B-3 and QPHT.6B-2 had the highest QTL stability (Fig. [2](#page-15-0)) and have previously been identified in other QTL mapping studies (Gao et al. [2015;](#page-23-0) Klahr et al. [2007;](#page-23-0) Huang et al. [2003](#page-23-0); Zhang et al. [2010](#page-24-0)). QPHT.4B-1 and QPHT.1D were also detected as M-QTLs in the RSH population with the beneficial allele derived from Roshan. These QTLs explained 16.1 and 8.3 percent of PHT variation, respectively. As shown in the joint genotype by environment analyses, nine QTLs were unstable across environments.

A total of 10 QTLs were identified for thousand kernel weight across environments in the three mapping populations. Joint genotype by environment analyses identified four QTLs (QTKW.3A, QTKW.5B, QTKW.7A-1, QTKW.7A-2) showing the greatest stability across environments. These results match those observed in earlier studies. Groos et al. [\(2003](#page-23-0)) in a detailed genetic analysis of TKW reported QTLs on chromosome 5B and 7A in 7 environments. They also found another QTL on chromosome 3A in a single environment, suggesting that it was unstable.

The ever-growing global population and limited agricultural land make the development of highyielding varieties an absolute priority for wheat breeders (Lobell et al. [2011;](#page-23-0) Ray et al. [2012](#page-24-0)). Therefore, the identification and validation of yieldrelated QTLs can facilitate improvement of highyielding varieties. In the present study, joint genotype by environment analyses revealed that QGYLD.3B, QGYLD.6A, QGYLD.1A were the most stable QTLs for GYLD (Fig. [2](#page-15-0)). As expected, the beneficial allele in 2 out of 3 stable QTLs associated with GYLD were derived from Roshan (high yield and salinity tolerant parent). These QTLs have been reported in previous studies (Groos et al. [2003](#page-23-0); Huang et al. [2003](#page-23-0); Azadi et al. 2015; Zhang et al. [2010](#page-24-0)). A single stable QTL (QHAI.2B) out of 6 was identified for HAI. Kumar et al. ([2007\)](#page-23-0) also found a QTL for harvest index in Chromosome 2B of wheat. As clear in the biplot analysis there were no stable QTLs for SPP, SPW and WKP (Fig. [2\)](#page-15-0), although several M-QTLs were detected for SPP, SPW and WKP in single environments. MAS should be applied with caution for such environment-specific QTLs.

Among the 7 identified QTLs for spike length, QSPL.3A showed a stable pattern across environments, as did QSPL.3A, which was the most stable QTL associated with SPL. To the best of our knowledge, the most stable quantitative trait loci for SPL (QSPL.3A) has not previously been reported. This novel QTL was identified in the RSH population with the positive allele derived from Roshan.

Two stable QTLs (QBYI.7A and QBYI.7B-1) were detected for biological yield (Fig. [2\)](#page-15-0). QTL on chromosome 7A were previously reported for BYI (Sardouie-Nasab et al. 2013; Kumar et al. [2007\)](#page-23-0). As far as we are aware, QBYI.7B-1, which is the most stable QTL for BYI detected in this study, has not previously been reported. Notably, the beneficial allele of QBYI.7B-1 was derived from Roshan.

In conclusion, we carried out QTL mapping for yield-related and morphological traits of wheat, with the aim of identifying QTLs under salinity stress and their effects in different genetic backgrounds, as well as their epistatic and environmental interactions. Overall, in the independent analysis, we detected 92 putative M-QTLs associated with 9 different yieldrelated and morphological traits. Whereas 191 epistatic QTLs were detected, only 3 epistatic QTLs involved M-QTLs. While we found seventeen environmentally stable QTLs for biological yield, grain yield, harvest index, plant height, spike length, and thousand kernel weight, only 4 QTLs were found across two genetic backgrounds and none across three. Genetic background independent QTLs with environmental stability will be most valuable for designing marker-assisted selection schemes in diverse environments. In the future it will be important to move beyond bi-parental mapping populations to genomewide association analyses using very large numbers of SNP markers, with the goal of enabling genomic selection for salt tolerance in wheat.

Ultimately, these findings have important implications for developing marker-assisted selection strategies for wheat breeding under salinity stress. The consistent effect of highly stable QTLs across different environments offers great opportunities for further functional genomics analysis to characterize genes for improving wheat yield under salinity stress.

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QTL \times QTL and genotype \times environment interactions. J Cereal Sci 56(2):432–439

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