In the presence of population structure: From genomics to candidate genes underlying

local adaptation

Running title: Genomic signatures of local adaptation

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Abstract

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36 Understanding the genomic signatures, genes, and traits underlying local adaptation of organisms

37 to heterogeneous environments is of central importance to the field evolutionary biology. Mixed

38 linear mrsodels that identify allele associations to environment, while controlling for genome-

39 wide variation at other loci, have emerged as the method of choice when studying local

40 adaptation. Despite their importance, it is unclear whether this approach performs better than

41 identifying environmentally-associated SNPs without accounting for population structure. To

42 examine this, we first use the mixed linear model GEMMA, and simple Spearman correlations,

43 to identify SNPs showing significant associations to climate with and without accounting for

44 population structure. Subsequently, using Italy and Sweden populations, we compare evidence of

45 allele frequency differentiation (F_{ST}), linkage disequilibrium (LD), fitness variation, and

46 functional constraint, underlying these SNPs. Using a lenient cut-off for significance, we find

47 that SNPs identified by both approaches, and SNPs uniquely identified by Spearman

48 correlations, were enriched at sites showing genomic evidence of local adaptation and function

49 but were limited across Quantitative Trait Loci (QTL) explaining fitness variation. SNPs

50 uniquely identified by GEMMA, showed no direct or indirect evidence of local adaptation, and

51 no enrichment along putative functional sites. Finally, SNPs that showed significantly high F_{ST}

52 and LD, were enriched along fitness QTL peaks and cis-regulatory/nonsynonymous sites

53 showing significant functional constraint. Using these SNPs, we identify genes underlying

54 fitness QTL, and genes linking flowering time to local adaptation. These include a regulator of

55 abscisic-acid (*FLDH*) and flowering time genes *PIF3*, *FIO1*, and *COL5*.

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Introduction

61 Populations of a species may inhabit different environments where local selection pressures

62 favor a combination of (multivariate) phenotypes (Leimu and Fischer 2008; Conover, et al. 2009;

63 Hereford 2009; Savolainen, et al. 2013). Once locally adapted, the resident genotype is expected,

64 on average, to have a higher relative fitness than a foreign genotype (Kawecki and Ebert 2004).

65 Despite the widespread evidence of local adaptation in many taxa (Leimu and Fischer 2008;

66 Jeong and Di Rienzo 2014; Arguello, et al. 2016), our understanding of the traits involved, its

67 genetic basis, and its environmental underpinnings is still at an infant stage (Savolainen, et al.

68 2013; Tiffin and Ross-Ibarra 2014; Wadgymar, et al. 2017).

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70 In a variety of species, reciprocal transplant and common garden/laboratory experiments have

71 showed significant adaptive differentiation between natural populations inhabiting different

72 environments (Via 1991; Hendry, et al. 2002; Savolainen, et al. 2007; Ågren and Schemske

73 2012; Kaufmann, et al. 2017; Phifer-Rixey, et al. 2018). Furthermore, in plants and animals,

74 mapping experiments have uncovered Quantitative Trait Loci (QTL) for traits that are thought to

75 underlie local adaptation (Colosimo, et al. 2004; Oakley, et al. 2014; Yang, et al. 2016; Ågren, et

76 al. 2017), in addition to QTL explaining fitness differences across environments (Ågren, et al.

77 2013; Anderson, et al. 2013). Despite the importance of QTL studies in providing direct

78 evidence for local adaptation (Ågren, et al. 2013), in many instances they provide a low

79 resolution for its genetic basis, and in practical terms are time consuming, expensive, and labor

80 intense (Joosen, et al. 2009).

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With the advent of low-cost, and fast, next generation sequencing (Henson, et al. 2012), higher

resolution population genomics approaches have emerged as the new means for examining the

genetic basis of local adaptation. (Lachance and Tishkoff 2013; Savolainen, et al. 2013; Tiffin

and Ross-Ibarra 2014; Sork 2017). In brief, these methods include: (a) identifying single

nucleotide polymorphisms (SNPs) showing significant allele frequency differentiation between

populations (F_{ST}) (Beaumont and Balding 2004; Foll and Gaggiotti 2008; de Villemereuil and

Gaggiotti 2015); (b) identifying genomic regions showing significant increases in linkage

disequilibrium (Jacobs, et al. 2016) or composite likelihood ratios for recent sweeps (DeGiorgio,

et al. 2016; Huber, et al. 2016); and (c) alleles showing significant correlations to

environment/climate (Hancock, et al. 2011; Jones, et al. 2012; Lasky, et al. 2012; Lasky, et al.

2014; Pluess, et al. 2016; Yeaman, et al. 2016; Monroe, et al. 2018; Price, et al. 2018). The latter

approach has gained particular attention because it can be implemented on the basis of individual

(as opposed to population-based) sampling, and furthermore it provides a direct link to

ecologically relevant factors (e.g., climate).

Despite the ability of population genomic methods to identify candidate genetic variation

underlying local adaptation, it is hard to disentangle the effects of selection from demographic

history (Lotterhos and Whitlock 2014; Hoban, et al. 2016). Geographically varying environments

can generate population structure in the regions of genes involved in adaptation, even under

conditions (e.g. high gene flow) that do not generate population structure at a genome-wide level

(McKay and Latta 2002). The degree to which population structure influences the patterns of

genome-wide LD and therefore the occurrence of false positives has emerged as a critical hurdle

(Platt, et al. 2010). To limit the number of spurious associations, studies usually estimate

population structure using different methods (Price, et al. 2010), incorporate population structure

(Yu, et al. 2006; Kang, et al. 2010; Wang, et al. 2011; Zhou and Stephens 2012) and/or

geographic structure (Lasky et al. 2012) into statistical models, and finally test whether certain

loci explain significantly higher variation in environment/climate than population structure itself

(Hancock, et al. 2011; Lasky, et al. 2012; Fischer, et al. 2013; Huber, et al. 2014; Lasky, et al.

2014; Monroe, et al. 2016; Rellstab, et al. 2017; Frachon, et al. 2018; Lasky, et al. 2018; Price, et

al. 2018). While such approaches may limit the number of false positives, they can also lead to

false negatives (Bergelson and Roux 2010; Anderson, et al. 2011). According to simulations

(Forester, et al. 2018), when selection is spatially autocorrelated, accounting for population

structure reduces the power to detect loci under selection (Forester, et al. 2018).

The negative effects of accounting for population structure, may explain the reduced signal of

genetic convergence to climate among distantly related conifers (Yeaman, et al. 2016).

Furthermore, in *Arabidopsis thaliana,* it may underlie the lack of significant associations

between climate-correlated SNPs and fitness QTL exhibiting genetic tradeoffs (Price, et al.

2018); and the lack of SNPs showing significant associations to drought survival among

Eurasian accessions (Exposito-Alonso, et al. 2018). Finally, in the plant *Capsella bursa-pastoris*,

accounting for population structure explained all variation in gene expression among ecotypes

that differed in important life-history traits such as flowering time and circadian rhythm

(Kryvokhyzha, et al. 2016).

In conjunction to population genomic signatures of selection or significant associations to

climate, genetic variation underlying local adaptation is expected to be enriched along sites that

are functional and influence fitness. SNPs showing significant associations to climate were found

to be significantly enriched among nonsynonymous, but also synonymous variation (Hancock, et

al. 2011; Lasky, et al. 2012). The enrichment among synonymous variation (which largely

evolve neutrally) maybe the result of linkage disequilibrium due to neutral processes but also

background selection (Charlesworth, et al. 1993) and/or hitchhiking (Gillespie 2000). A stricter

enrichment test will be one that controls for sequence conservation along coding and non-coding

sites. Sites that are highly conserved among species (Miller, et al. 2007; Haudry, et al. 2013;

Hupalo and Kern 2013), are assumed to be under functional/selective constraint and functionally

important — that is, due to purifying selection the number of tolerated mutations is limited

(Graur 2016). Therefore, SNPs showing significant evidence of local adaptation across highly

constraint sites are more likely to be true positives.

In the current study, we first examine how accounting for population structure in genome-wide

associations to climate may affect our ability to provide a comprehensive picture on the genetic

basis of local adaptation; and secondly, we use an approach that accounts for genetic signatures

of selection and functional constraint to detect potential genes underlying local adaptation.

More specifically, during the first phase we use 875 *A. thaliana* Eurasian accessions and identify

SNPs showing significant correlations to Minimum Temperature of Coldest Month

(Min.Tmp.Cld.M) using a mixed linear model that accounts for population structure (Zhou and

Stephens 2012) (GEMMA- Genome-wide Efficient Mixed Model Association) and simple

Spearman correlations (Spearman 1987) that did not account for population structure (we mainly

focused on Min.Tmp.Cld.M —a proxy to winter temperature— because of significant evidence

linking cold acclimation to local adaptation in wild populations (Ågren and Schemske 2012;

Oakley, et al. 2014; Gienapp, et al. 2017; Oakley, et al. 2018)). Using the two sets of SNPs, we

first separated them into ones identified by both methods (referred to as "Common" hereafter),

and ones uniquely identified by each approach (referred to as "GEMMA" and "Spearman"

hereafter). Thereafter, we compared evidence of local adaptation and function underlying the

three sets of SNPs. More specifically, using Italy and Sweden re-sequenced genomes, and QTL

explaining fitness variation between these populations (Ågren, et al. 2013), we examined: (a) the

level of allele frequency differentiation and linkage disequilibrium underlying SNPs showing

significant associations to climate before and after accounting for population structure; (b) how

these SNPs were distributed along LOD score peaks of 20 fitness QTLs (Ågren, et al. 2013); and

(c) how they were distributed along nonsynonymous and cis-regulatory sites showing significant

functional constraint among plants species of the Brassicaceae family (Haudry, et al. 2013).

During the second phase, we use SNPs showing significant evidence of local adaptation and

function, to identify potential genes underlying fitness QTL and flowering time variation

between Italy and Sweden populations. Flowering time is a life history trait that is thought to

play a significant role in local adaptation to climate (Hall and Willis 2006; Verhoeven, et al.

2008; Sandring and Agren 2009; Dittmar, et al. 2014; Ågren, et al. 2017), and whose genetic

basis has been thoroughly studied (Salomé, et al. 2011; Sasaki, et al. 2017). To re-examine

evidence linking flowering time to climate adaptation we used the following data: (1) a list of

genes that were experimentally shown to affect flowering time; (2) high confidence QTL

explaining flowering time variation between Italy and Sweden populations (Ågren, et al. 2017),

173   and (3) flowering time estimates for Arabidopsis Eurasian accessions (1001 Genomes

174   Consortium 2016).

Materials and Methods

Detecting associations to climate with and without accounting for population structure

To compare allele associations to climate with and without accounting for population structure

we focused on the climate variable Minimum Temperature of Coldest Month (Min.Tmp.Cld.M).

Using a SNP genotype matrix for a panel of 1,135 globally distributed accessions downloaded

from the 1001 Genomes database, we filtered out accessions from outside the native Eurasian

and North African range of *A. thaliana*, as these accessions may have weaker patterns of local

adaptation (Lasky, et al. 2012). We also filtered out accessions that were likely laboratory

escapees or contaminants (Pisupati, et al. 2017), leaving 875 accessions. After we filtered for

biallelic SNPs with minor allele frequency >0.05, we tested association with home climate of

ecotype and tested for potential confounding effects of population structure using the software

"gemma" (Zhou and Stephens 2012). The parameters used in gemma were a MAF of 0.05

(default 0.01) and a missingness threshold of 0.05. For the linear mixed model option, we used

Wald test (default) to test for significant associations to climate. We tested models where home

climate was a function of SNP allele, and the association p-values we report are for the null

hypothesis that the mean climate occupied by the two alleles is equal (Lasky, et al. 2014). Using

the same set of SNPs we estimated correlations to climate using simple "Spearman" correlations

(Spearman 1987) and not accounting for population structure. To estimate p-values for the

Spearman correlations we used the 'cor.test' function implemented in R (Team 2009).

Estimates of selection and candidate functional variation underlying populations in North

Sweden and South Italy.

In addition to associations to climate, genomic signatures of selection were examined in North

Sweden and South Italy populations that represent the most northern and southern tips of

Eurasia. The accessions used, including latitude and longitude coordinates are found in the

Supplementary data file. Evidence of local adaptation/selection across SNPs between Italy and

Sweden populations was measured using absolute allele frequency differentiation ($F_{ST} \approx$

$|f_{N.Sweden} - f_{S.Italy}|$) and linkage disequilibrium (LD) between a SNP and its neighboring SNPs

with a 20kb window. LD was measured using the package 'PLINK' (Purcell, et al. 2007) and it

was estimated as the mean square coefficient of correlation ($\overline{r^2}$). For evidence of recent sweeps

we used previously calculated (Price, et al. 2018) Composite likelihood Ratios (CLR's) that were

computed using Sweepfinder2 (DeGiorgio, et al. 2016). We focused on CLR's in North Sweden

because in other populations signals identified were very weak (Long, et al. 2013; Huber, et al.

2014; Price, et al. 2018).

To narrow down SNPs to ones that are more likely to underlie differences in function/expression

of protein-coding genes we focused on cis-regulatory and nonsynonymous variation that was

found along sites showing significant functional constraint. We regarded cis-regulatory SNPs as

those found within 1 kb upstream from the transcriptional start site of a gene (Zou, et al. 2011;

Pass, et al. 2017), unless these sites were found in transcribed regions of other genes (in which

case they were excluded). To call nonsynonymous variation we used bi-allelic sites, we used a

publicly available python script (callSynNonSyn.py; archived at https://github.com/kern-lab/),

and gene models downloaded from the TAIR database (TAR10 genome release) (Berardini, et al.

2015). To annotate regions showing significant functional constraint across the *A. thaliana*

genome we used phastCons scores (Siepel, et al. 2005) derived using a nine-way alignment of

Brassicaceae species from the study by Haudry et al. (2013). We defined conserved regions as

those with a score >=0.8 over blocks of >=10 nucleotides.

Fitness and flowering time QTL underlying Italy and Sweden populations

Quantitative trait loci explaining fitness variation between natural *A. thaliana* Italy and Sweden

populations were retrieved by the study of Ågren et al. (2013). These 20 fitness QTL were

assembled into 6 genetic tradeoff QTL (Ågren, et al. 2013), however we treated them as

independent given the very long genetic distances between fitness QTL peaks (Supplementary

data). Furthermore, we retrieved high confidence QTL explaining flowering time variation

between these populations (Ågren, et al. 2017) (Supplementary data).

Circular permutation tests

To test whether SNPs showing significant correlations to Min.Tmp.Cld.M and/or SNPs showing

high F_{ST} and LD between Italy and Sweden populations are enriched along QTL peaks and

among cis-regulatory/nonsynonymous variation at sites showing significant functional constraint

we used a 1,000 circular permutations (Fig. 1).

Fig. 1. Diagram of circular permutations used to build null distributions for various measures. The first step involves choosing a random location along the genome and shift p-values or allele frequency differentiations. In the next step, when examining climate associations, we chose SNPs with a p-value less than a specified threshold. We also samples of SNPs showing a high F_{ST} and LD. SNPs showing "significant" correlations to climate were further partitioned into those showing "significance" using both Spearman and GEMMA correlations ("Common") or were unique to each approach ("GEMMA" or "Spearman"). Using the final set of SNPs, we computed various measures of interest.

Fig. 1 depicts the steps involved in the circular permutations. In brief, during the first step p-

values associated with climate correlations or allele frequency differentiations were shifted based

on a random SNP along the genome. The second step involved choosing SNPs showing

"significant" associations to climate (p-value < 1st percentile of Spearman/GEMMA p-value

distributions), or high allele frequency differentiations and LD ($|f_{N.Sweden} - f_{S.Italy}|$>0.70 and

LD>0.19: 0.70 and 0.19 represent the 95th percentiles of the distributions). For climate

associations, SNPs were partitioned into those showing "significance" using both Spearman and

GEMMA associations ("Common") or those showing "significance" using only one approach

("GEMMA" or "Spearman").

The final sets of SNPs were used to estimate the following measures: (a): % of SNPs found

within a certain distance (100, 200, ….600 kb) upstream and downstream of the 20 fitness QTL

peaks; and (b) the proportion of cis-regulatory and nonsynonymous SNPs that were within

regions showing significant functional constraint.

Sliding window analysis of chromosomal variation SNPs showing evidence of local adaptation

To detect chromosomal regions with a high proportion of SNPs showing significant evidence of

local adaptation we used a sliding window approach. Specifically, for a window size of 20kb and

a step size of 1kb we estimated the ratio of SNPs showing a specific requirement (e.g.,

$f_{N.Sweden} - f_{S.Italy}|>0.70$ and LD>0.19) over the total number of SNPs within a 20kb window.

Flowering time estimates for A. thaliana Eurasian accessions and candidate flowering time

genes

Estimates of flowering time for the 835 Eurasian *A. thaliana* accessions were downloaded from

the study by Alonso-Blanco et. al (2016) (1001 Genomes Consortium 2016). In brief, plants

were grown in growth chambers with the following settings: after 6 days of stratification in the

dark at 4ºC, constant temperature of 16°C with 16 hours light / 8 hours darkness, 65% humidity.

Flowering time was scored as days until first open flower. See Alonso-Blanco et al. (2016) for

further details. A set of genes that were experimentally verified to affect flowering time was

downloaded from Prof. Dr. George Coupland website

(https://www.mpipz.mpg.de/14637/Arabidopsis_flowering_genes)

Constructing rooted gene trees
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To build neighbor joining trees of genes showing significant local adaptation we downloaded 1:1

orthologs between *Arabidopsis thaliana* and outgroups *Arabidopsis lyrata* and *Capsella rubella* from

the Phytozome database (Goodstein, et al. 2012) and after aligning the coding sequences with

MAFFT (Katoh and Toh 2008) we used MEGA (Tamura, et al. 2013) to build a rooted gene trees.

Results

Genomic signatures of local adaptation and selection captured by climate associations in Italy
and Sweden populations

Genome wide correlations to Minimum Temperature of Coldest Month (Min.Tmp.Cld.M) were

examined using simple Spearman correlations (Spearman 1987) and a mixed model called

GEMMA (Zhou and Stephens 2012) that accounted for putative population structure. Fig. S1

depicts the p-value distributions that were obtained when testing for significance using GEMMA

and Spearman correlations. P-values underlying Spearman correlation were skewed towards very

low p-values; many of which are likely false positives. Nonetheless, we compared the results

obtained by the two methods using different percentiles of the p-value distributions as cutoffs for

significance (10th, 5th, 1st percentiles). For significant SNPs that were segregating between North

 Sweden and South Italy populations the percent of SNPs that were identified by both approaches

296   ("Common") at the three significance levels was ~20% (Fig. S2).

Fig. 2. Comparing allele frequency differentiation and linkage disequilibrium across SNPs
showing significant associations to Min.Tmp.Cld.M. (A-B) Average absolute allele frequency
differentiation ($|f_{N.Sweden} - f_{S.Italy}|$) and linkage disequilibrium ($\overline{r^2}$) was significantly higher
the genome average (dotted lines) across SNPs identified by both Spearman and GEMMA
correlations ("Common") and SNPs uniquely identified by Spearman correlations ("Spearman").
These sets of SNPs also showed a decrease in $|f_{N.Sweden} - f_{S.Italy}|$ and $\overline{r^2}$ decreased as the the
threshold for significance became more lenient (1→10 %) (95% CI's which are not visible were
estimated using a bootstrap approach). (C-E) A positive association between $|f_{N.Sweden} -$
$f_{S.Italy}|$ and $\overline{r^2}$ across the three sets of SNPs showing significant correlations to Min.Tmp.Cld.M
when using the 1st percentile of the p-value distributions (Fig. S1) as the significance level.

When comparing the average absolute allele frequency differentiation $|f_{N.Sweden} - f_{S.Italy}|$ and

LD ($\overline{r^2}$) across SNPs that were unique to each approach ("Spearman" or "GEMMA") and SNPs

identified by both methods ("Common") the set of "Common" and "Spearman" SNPs showed

significantly higher allele frequency differentiation and LD than the genome average (Fig 2A-

2B). On the other hand, SNPs that were unique to "GEMMA" did not show any large differences

in F_{ST} and LD from the genome average (Figs 2A-2B). Furthermore, across "Common" and

"Spearman" SNPs we see a decrease in ($|f_{N.Sweden} - f_{S.Italy}|$) and LD as the threshold of

significance becomes less stringent (Figs 2A-2B). This is indicative that stronger associations

capture SNPs showing stronger evidence of local adaptation and recent selection. Therefore, for

any further tests we used the set of SNPs that were significant using the 1st percentile of the p-

value distributions as the cutoff.

Local adaptation is expected to lead to an increase in allele frequency differentiation and LD at

and near the site under selection; in other words, we would expect a positive correlation between

$|f_{N.Sweden} - f_{S.Italy}|$ and LD. As shown in Figs 2C-2E all three sets of SNPs showed significant

associations between $|f_{N.Sweden} - f_{S.Italy}|$ and LD. On the other hand, while "Spearman"

SNPs were enriched in SNPs showing a $|f_{N.Sweden} - f_{S.Italy}|$ near fixation (>0.90) the level of

LD was lower (Fig. 2D) (also reflected in Fig. 2B). Finally, as expected given the small

deviations from the genome average (Figs 2A-2B), "GEMMA" SNPs showed the poorest

associations with a small sample of SNPs showing a $|f_{N.Sweden} - f_{S.Italy}|$ between 0.60-0.80

and LD between 0.30-0.40 (Fig. 2E). Taken together, indicate indicate that "Common" and

"Spearman" SNPs capture higher population genomic evidence of local adaptation, than SNPs

uniquely identified by GEMMA.

Detecting recent selection underlying fitness QTL is significantly reduced when accounting for

population structure in GWA to climate

Direct evidence of local adaptation was shown in a study by Ågren et al. (2013) in which they

identified 20 QTL explaining fitness variation between Italy and Sweden populations

(Supplementary data). To examine population genomic evidence of local adaptation underlying

these QTL we first examined $|f_{N.Sweden} - f_{S.Italy}|$ and LD which are measures specific to Italy

and Sweden populations. If the peaks of the QTL identified, are on average, near the site under

selection we would expect a significant enrichment of high F_{ST} and LD SNPs. Using different

window sizes (100, 200, ...600 kb) from the QTL peaks we compared the observed proportion

of high F_{ST} SNPs ($|f_{N.Sweden} - f_{S.Italy}|$ >0.70 —0.70 represents the 95th percentile of the

distribution), and the proportion of high F_{ST} and LD SNPs (LD>0.19 — 0.19 represents the 95th

percentile of the distribution) to the expected proportion derived using a circular permutation

test. As expected, we observed a significantly high proportion of high F_{ST} (>0.70) SNPs and

high F_{ST} and high LD SNPs (Figs 3A-3B). A significant proportion was also observed at 200 kb,

but as window sizes became larger the proportions became insignificant (<95th percentile) and

normalized to the genome average.

Next, we performed the same test using SNPs showing significant associations to climate, and

SNPs that showing significant associations to climate and a high F_{ST} and high LD. When

considering only associations to climate (Fig. S3) we find an enrichment of "Common" and

"Spearman" SNPs (Fig. S3), but not "GEMMA" SNPs. On the other hand, when we also

considered high F_{ST} and high LD, none of the SNPs showed an enrichment (Fig. 3C). Among the

three sets, Spearman SNPs showed the highest observed proportion (>80th percentile). To

determine whether the significantly lower proportion of "Common" SNPs showing a high F_{ST}

and high LD was due to the stringency of our cutoff, we calculated the average F_{ST} and LD for

SNPs with an $|f_{N.Sweden} - f_{S.Italy}|$<0.70 and $\overline{r^2}$<0.19. The average $|f_{N.Sweden} - f_{S.Italy}|$

(≈0.26) and LD (≈0.06) were near or lower than the genome average (Fig. 2A-2B) to be

considered as strong candidates underlying local adaptation.

Fig. 3. Distribution of SNPs showing population genomic evidence of local adaptation along
fitness QTL peaks. (A) The observed proportion of SNPs showing significantly high allele
frequency differentiation ($|f_{N.Sweden} - f_{S.Italy}| > 0.70$) (red line) in comparison to a
permutation distribution of random proportions. The observed proportion was greater than the
95th percentile. (B) The observed proportion of SNPs showing a $|f_{N.Sweden} - f_{S.Italy}| > 0.70$
and significantly high linkage disequilibrium ($\overline{r^2}$>0.19), was also greater than the 95th percentile
of random proportions. (C) The observed proportions of SNPs showing significant associations
to climate, in addition to a $|f_{N.Sweden} - f_{S.Italy}| > 0.70$ and a $\overline{r^2}$>0.19. The proportion of
"Common" and "GEMMA" SNPs near QTL peaks was very low, while the proportion
"Spearman" SNPs was greater than the 80th percentile of the distribution but less than the 95th.

Given that "Common" SNPs did not show an enrichment within 100kb of the 20 fitness QTL

peaks examined (Supplementary data), we searched whether any of these were within the six

tradeoff QTL that each span a large genomic region (Supplementary data). As shown in Fig. S4,

most of the high F_{ST} and high LD "Common" SNPs (181/209) were found within a 60kb region

(14,719-14,781Mb) of a single genetic tradeoff (GT) QTL (GT QTL 2:2) (Fig. S4). Apart from

being limited to a single GT QTL, given the multiple fitness QTL within GT QTL 2:2 (which

spanned a length of ~4Mb); the multiple regions showing significant recent sweeps in Sweden;

and the large number of windows showing a high proportion of high F_{ST} and LD SNPs; it is

highly unlikely that the "Common" set of SNPs cover all the causative genetic variation within

GT QTL 2:2.

To further test for enrichment of "GEMMA" SNPs showing significant associations to climate

and within 100 kb of fitness QTL peaks, we used an additional three climate variables (Table

S1). Using a lenient cutoff for significance (FDR<0.1), we only identified a few additional SNPs

within 100 kb of fitness QTL.

All in all, our results indicate that accounting for population structure when performing GWA to

climate significantly reduces our ability to capture recent selection underlying fitness QTL.

All but "GEMMA" SNPs show enrichment at cis-regulatory and nonsynonymous sites showing

significant functional constraint

SNPs underlying local adaptation are expected to be significantly enriched at sites that affect

function and/or expression of protein coding genes. Using the three sets of SNPs showing

significant associations to climate ("Common", "GEMMA", and "Spearman") and SNPs

showing high F_{ST} and LD (abbreviated as "F_{ST}&LD") we examined their distribution among

cis-regulatory and nonsynonymous SNPs at sites showing significant functional constraint

among Brassicaceae plants (Haudry, et al. 2013) (phastCons>0.8).

402

403 **Fig. 4**. Proportion of cis-regulatory and nonsynonymous SNPs showing population genomic
404 evidence of local adaptation and function (A) Red dots indicate the observed proportion of
405 nonsynonymous SNPs showing associations to climate ("Common", "GEMMA", "Spearman")
406 or high F_{ST} and LD ("F_{ST} &LD") and within coding regions showing significant functional
407 constraint (phastCons>0.8). Expectations and 95% CI's were derived using circular permutations
408 (B) The observed proportions of cis-regulatory SNPs showing population genomic evidence of
409 local adaptation and found within conserved regions.

410

411 As shown in Figs 4A & 4B, the proportions of nonsynonymous/cis-regulatory "Common",

412 "Spearman", and high "F_{ST}&LD" SNPs, was significantly higher than expected by chance. On

413 the other hand, "GEMMA" SNPs did not show a significant enrichment in any of the categories.

414 When considering all the results obtained so far (Figs 2-4), unique "Spearman" SNPs seem to

415 capture additional genetic variation underlying local adaptation (i.e., in addition to "Common"

416 SNPs), while unique "GEMMA" SNPs do not.

417

418 *Flowering time genes showing significant evidence of local adaptation and underlying flowering*

419 *time QTL.*

420

Given the significant enrichment of high F_{ST} and LD SNPs, along QTL peaks (Fig. 3B) and

conserved cis-regulatory and nonsynonymous sites (Figs 4A & 4B), we used them to detect

potential genes that may underlie fitness QTL (note: we only focused on variants within 100kb of

their peaks), in addition to examining evidence of local adaptation underlying a list of ~170

genes affecting flowering time (Supplementary data). To further narrow down on SNPs that are

more likely to underlie the fitness QTL examined, we only considered variation that segregated

between the parents used to derive the RIL's (Ågren, et al. 2013). SNPs between the parental

genomes were called in a previous study (Price, et al. 2018).

Our analysis resulted in 25 genes within 100 kb of fitness QTL peaks and spanning three genetic

tradeoff QTL (2:2, 4:2, 5:5) (Table S2). Many of these were involved in interesting biological

processes such as: response to different abiotic stress factors and the abscisic-acid signaling

pathway which is important in abiotic stress response (Tuteja 2007) (Table S2). Among these

genes, two of them (AT4G33360 (*FLDH*), AT4G33470 (*HDA14*)) showed strong expression

GxE interactions (GxE interactions were identified in a previous study (Price, et al. 2018)) when

Italy and Sweden plants were grown under cold acclimation conditions (4 °C) for two weeks

(Gehan, et al. 2015). Interestingly, *FLDH* is a negative regulator of the abscisic acid signaling

pathway (Bhandari, et al. 2010) . As shown in Fig. 5A this gene was within a region of a genetic

tradeoff QTL that showed a significantly high proportion of high F_{ST} and high LD SNPs.

Expression of *FLDH* under control and cold acclimation conditions was significantly lower in

Sweden than Italy plants (Fig. 5A).

443   Among the set of flowering time genes, we identified three (AT1G09530 (*PIF3*), AT2G21070

444   (*FIO1*), and AT5G57660 (*COL5*)) that contained high F_{ST} and LD nonsynonymous SNPs within

445   conserved coding regions. Among the three genes, *PIF3* was found along a chromosomal region

446   that showed the highest CLR for a recent sweep in Sweden and a high density of SNPs showing

447   high F_{ST} and high LD (Fig. 5B).

448

449

450 **Fig. 5**. Fitness QTL and flowering time genes showing significant evidence of local adaptation
451 along conserved cis-regulatory and nonsynonymous sites. (A) *FLDH* a negative regulator of
452 ABA (Bhandari, et al. 2010) was found within a genetic tradeoff QTL 4:2 and 100 kb from a
453 fitness QTL peak (red and blue arrows represent QTL where the Sweden genotype had lower
454 fitness in Italy and higher fitness in Sweden, respectively). *FLDH* was found within a region
455 showing a high proportion of high F_{ST} and high LD SNPs. In Italy and Sweden plants it showed
456 strong expression GxE interactions under control and cold acclimation conditions for two weeks
457 (FPKM: Fragments Per Kilobase Million). (B) *PIF3* is a phytochrome interacting factor that has

458	been found to affect flowering time (Oda, et al. 2004) and was found underlying a region along
459	chromosome 1 that showed the largest Composite Likelihood Ratio (CLR) of a recent sweep in
460	Sweden and windows with a high proportion of high F_{ST} and high LD SNPs. A rooted phylogeny
461	of the *PIF3* coding region indicated that Eurasian accessions sharing the same allele as the
462	Sweden parent (blue dot) show significantly higher flowering time than accessions sharing the
463	same allele as the Italy parent (red dot). (C) *COL5* is another gene that has been found to affect
464	flowering time (Hassidim, et al. 2009) and in which Eurasian accessions show significant genetic
465	differentiation and segregation in flowering time. This gene is also found within previously
466	identified flowering time QTL (FlrT-5:4) (Ågren, et al. 2017) in which the Sweden genotype was
467	associated with longer flowering time in both Italy and Sweden

been found to affect flowering time (Oda, et al. 2004) and was found underlying a region along

chromosome 1 that showed the largest Composite Likelihood Ratio (CLR) of a recent sweep in

Sweden and windows with a high proportion of high F_{ST} and high LD SNPs. A rooted phylogeny

of the *PIF3* coding region indicated that Eurasian accessions sharing the same allele as the

Sweden parent (blue dot) show significantly higher flowering time than accessions sharing the

same allele as the Italy parent (red dot). (C) *COL5* is another gene that has been found to affect

flowering time (Hassidim, et al. 2009) and in which Eurasian accessions show significant genetic

differentiation and segregation in flowering time. This gene is also found within previously

identified flowering time QTL (FlrT-5:4) (Ågren, et al. 2017) in which the Sweden genotype was

associated with longer flowering time in both Italy and Sweden

Eurasian accessions sharing a similar allele as the Sweden parent showed longer flowering time

than accessions sharing the same allele as the Italy parent (Fig. 5B). The same pattern was

observed when examining *COL5* (Fig. 5C), a flowering time gene which was also found within a

flowering time QTL (FlrT-5:4, Supplementary data). According to FlrT-5:4, the Sweden

genotype was associated with longer flowering time in both Italy and Sweden (Ågren, et al.

2017). In conjunction, with its overlap to a genetic tradeoff QTL (Ågren, et al. 2017), indicates a

possible role in fitness tradeoffs. Studies have attributed flowering time variation within FlrT-5:4

to *VIN3* (1001 Genomes Consortium 2016; Ågren, et al. 2017). Although it may be an additional

candidate we did not find any significant genetic differentiation and selection along coding and

cis-regulatory sites of *VIN3*.

When examining flowering time genes with high F_{ST} and LD along cis-

regulatory/nonsynonymous sites that did not show significant functional constraint we identified

an additional nine genes; four of which were found within flowering time QTL (**FlrT**):

AT1G14920 (GAI); AT1G53090 (SPA4); AT2G22540 (SVP); AT2G47700 (RFI2);

AT4G32980 (ATH1-**FlrT4:1**); AT5G24470 (PRR5-**FlrT5:2**); AT5G62640 (ELF5);

AT5G65050 (MAF2- **FlrT5:5**); and AT5G65060 (MAF3- **FlrT5:5**). ATH1 was found in

genetic tradeoff QTL 4:2, while genes MAF2, and MAF3 were found within genetic tradeoff

QTL 5:5 and within 100 kb of fitness QTL peaks.

Discussion

In the quest to study the genetic basis of local adaptation using genome wide associations to

environment, linear mixed models have emerged as a powerful tool given their ability to account

for population structure while testing for significant associations (Yu, et al. 2006; Kang, et al.

2008; Kang, et al. 2010; Zhou and Stephens 2012). Although they provide a robust statistical

framework for removing many false positives, the current study shows that such an approach

may significantly limit our ability to understand the polygenic basis of local adaptation.

SNPs showing significant associations to climate after accounting for population structure, were

not in line with high F_{ST} and LD SNPs that showed a significant enrichment along fitness QTL

peaks and coding/noncoding sites under functional constraint. Since these QTL are of large

effect (Ågren, et al. 2013), the lack of significant associations is less likely to be a result of many

alleles having a small effect on fitness. A more likely explanation is that accounting for

population structure using genetic relatedness estimated from genome-wide SNPs, can lead to a

significant number of false negatives. *Arabidopsis thaliana* however, is a simple, highly inbred

species —to correctly assess the impact of accounting for population structure when examining

the genetic basis of local adaptation there needs to be examination of other species with more

complex life-history traits and evolutionary dynamics.

A large portion of SNPs that showed significant associations to climate, and SNPs that showed

high F_{ST} and LD between Italy and Sweden populations were enrichment among

nonsynonymous/cis-regulatory variation at sites showing significant functional constraint. These

results, further support an important role of cis-regulatory (Lasky, et al. 2014; Siepel and Arbiza

2014; Li and Fay 2017; Price, et al. 2018; Sackton, et al. 2019) and nonsynonymous variation

(Nachman, et al. 2003; Coop, et al. 2009; Lasky, et al. 2012; Huber, et al. 2014; Svetec, et al.

2016; Price, et al. 2018) in adaptation. Among the list of candidate genes underlying fitness QTL

and showing significant evidence of local adaptation at functionally constraint sites, we

identified *FLDH*. *FLDH* is a negative regulator of abscisic-acid signaling (Bhandari, et al. 2010),

that showed strong GxE interactions between Italy and Sweden plants under cold acclimation

conditions. Abscisic-acid signaling is known to play an important role in abiotic stress response

(Tuteja 2007), with many studies supporting its role in local adaptation to climate (Keller, et al.

2012; Lasky, et al. 2014; Kalladan, et al. 2017; Ristova, et al. 2017).

In addition to abscisic-acid signaling, our results provide further support for the important role of

flowering time in local adaptation to climate. Among a list of genes that were experimentally

shown to affect flowering time, we identified three genes (*PIF3*, *FIO1*, and *COL5*) that showed

significant evidence of local adaptation and functional constraint along nonsynonymous sites.

FIO1 was previously shown to contain SNPs that showed significant associations to flowering

time among natural Swedish lines (Sasaki, et al. 2015) and *COL5* was located within a QTL that

explains flowering time variation among Sweden and Italy recombinant inbred lines (Ågren, et

al. 2017). Finally, *PIF3,* a transcription factor that interacts with phytochromes (Soy, et al.

2012), has been implicated in multiple biological processes including early hypocotyl growth

(Monte, et al. 2004), photomorphogenesis (Dong, et al. 2017), flowering time (Oda, et al. 2004),

and regulation of physiological responses to temperature (Jiang, et al. 2017). This highly

conserved transcription factor was found within a large region that showed significant evidence

of local adaptation. This chromosomal region may involve a single causative variant, or a group

of linked genes that interact with *PIF3 and* were under selection because they contributed to

building an advantageous phenotype (Barton and Bengtsson 1986; Yeaman and Whitlock 2011).

When ignoring functional constraint, we identify a list of addition flowering time genes showing

significant evidence of local adaptation along nonsynonymous/cis-regulatory sites. Genes such

as SVP, MAF2, and MAF3 were previously associated with flowering time variation among

natural *Arabidopsis* accessions (Caicedo, et al. 2009; Sasaki, et al. 2015). Although adaptation

may involve sites that are not deeply rooted and/or under strong functional constraint, including

additional plant genomes when estimating sequence conservation across species may increase

our power to detect functionally important regions. As shown by studies examining adaptation in

species ranging from bacteria (Maddamsetti, et al. 2017) to birds (Sackton, et al. 2019),

addressing functional constraint can improve our understanding of its genetic basis.

Finally, the current study shows that we need a new statistical framework to examine genome

wide associations to environment, and furthermore, it increases our understanding on the genes

and traits that may underlie local adaptation in *A. thaliana*.

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Data accessibility statement

In our dryad submission we included:

(1) For positions segregating between South Italy and North Sweden we included the
following statistics: Fst, LD, GEMMA p-values, Spearman p-values
(2) Composite likelihood ratios for recent sweeps in Sweden
(3) Climate data for all the 1,135 *A. thaliana* re-sequenced genomes that have been recently
published (1001 Genomes Consortium 2016).
(4) Conserved coding regions
(5) Conserved non-coding regions

https://datadryad.org/review?doi=doi:10.5061/dryad.9vd6465

Author contributions

Nicholas Price: designed research, performed research, analyzed data, wrote the paper

Lua Lopez: performed research, reviewed paper

Adrian E. Platts: performed research, reviewed paper

Jesse R. Lasky: performed research, reviewed paper

John K. McKay: reviewed paper