Cis*-regulation of gene expression between sexes and life stages in *Rumex hastatulus

Meng Yuan[1,†], Bianca M. Sacchi[1], Baharul I. Choudhury[1,2], Spencer C. H. Barrett[1], John R.

Stinchcombe[1,*], Stephen I. Wright[1,*]

[1]Department of Ecology and Evolutionary Biology, University of Toronto, Toronto, ON, CA

[2]Department of Biology, Queen's University, Kingston, ON, Canada

*These authors made equal contributions.

†Corresponding author: E-mail: my.yuan@mail.utoronto.ca

Abstract

The potential for conflict between sexes and life stages while sharing predominantly the same

genome has important evolutionary consequences. In dioecious angiosperms, genes beneficial

for the haploid pollen stage may reduce the fitness of diploid offspring of both males and

females. However, we still lack an understanding of the extent of shared genetic architecture for

gene expression between the sexes or life stages in plants, a key component for predicting the

scope for conflict. We performed expression quantitative trait loci (eQTL) mapping to test if

standing variation affects sexes and life stages differently using a population sample of the

dioecious outcrossing plant *Rumex hastatulus*. We compared effect sizes and allele frequencies

of *cis*-eQTLs in male and female leaf tissues and pollen and tested for genotype-by-sex

interactions for gene expression. We found stronger shared genetic architecture between sexes

than between the life stages. In addition, comparisons of the site frequency spectra for *cis*-eQTLs

to a null distribution found no evidence for a genome-wide pattern consistent with purifying

selection. Rare alleles had both up- and down-regulation of gene expression. Our results suggest

that any conflict over optimal gene expression between pollen and leaves may be easily resolved

due to their distinct genetic architectures, whereas there is more scope for conflict between the

sexes in gene expression for leaves, which earlier studies indicate are sexually dimorphic. Our

study highlights the use of eQTLs to investigate selection on gene expression and the evolution

of conflict between sexes and life stages in dioecious species.

Keywords: *cis*-regulatory variation, eQTL, selective pressure, antagonistic pleiotropy

Introduction

Evolutionary conflict may arise when different sexes or life-cycle phases of an organism have different fitness optima while sharing a common genome (Ewing 1977; Arnqvist and Rowe 2005; Haig and Wilczek 2006; Schärer et al. 2015). For example, sexual conflict occurs when males and females in dioecious species have different fitness optima involving reproduction, and this can drive sexual dimorphism in phenotypic traits (Lande 1980; Bonduriansky and Chenoweth 2009). In plants, the diploid and haploid phases of the life cycle (i.e., sporophytes and gametophytes respectively, we use "life stages" to refer to these phases) are distinct in their morphology, physiology, and development despite sharing extensive overlap in gene expression, creating potential for genetic trade-offs (Haig and Wilczek 2006; Beaudry et al. 2020). Both sexual and life-stage conflict have been suggested to generate balancing selection and stable genetic variation under some conditions (Kidwell et al. 1977; Immler et al. 2012). However, we lack comprehensive understanding of the traits and genetic architecture underlying the conflict between sexes or life stages. Here, we use expression quantitative trait locus (eQTL) mapping to identify genome-wide *cis*-regulatory variation and investigate the extent of shared genetic architecture between sexes and life stages and the potential for sexual and life-stage conflict in a dioecious plant.

Current empirical examples of life-stage conflict often involve both sexes (i.e., a conflict both between the sexes and life stages). For example, alleles beneficial for haploid gametophytic competition were shown to reduce the fitness of female diploid offspring in the hermaphroditic annuals *Clarkia* (Travers and Mazer 2001) and *Collinsia* (Lankinen and Kiboi 2007; Lankinen et al. 2017). Sexual conflict independent of life stage differences has been observed in several plant species (e.g., Delph et al. 2011; Duffy et al. 2021; Wang et al. 2021), but genomic tests of sexual conflict in plants remain limited compared to animals (but see Delph et al. 2022). Gene expression is an important molecular trait underlying phenotypic variation. While direct tests of conflict require measurements of fitness which is often laborious and challenging, sexual or life-stage dimorphism in gene expression has been widely used to indirectly study conflict (Mank 2017; Yuan et al. 2025). With the considerable potential for both sexual and life-stage conflict in plants, whether there is a greater likelihood for one type of conflict than the other, or whether one type of conflict is more resolved than the other, remains unanswered. Thus, plants offer

excellent systems to study the evolution of conflict between sexes and life-cycle phases in a

single species.

The potential for future conflict, i.e., whether new mutations and standing variation are more

likely to be pleiotropic, depends on the degree of shared genetic architecture underlying

phenotypic traits between sexes or life stages. Genetic architecture describes how genetic

variation shapes phenotypic differences, including the number and effect sizes of contributing

genes. When both sexes share most of the genetic architecture underlying a trait (i.e., a positive

and high intersexual genetic correlation r_{mf}), there is strong potential for ongoing conflict in the

presence of antagonistic selection, and the evolution of sexual dimorphism is constrained (Lande

1980; Poissant et al. 2010; Wyman et al. 2013). Genetic covariances between sexes inferred

through gene expression studies in *Drosophila* suggest considerable scope for ongoing conflict

(Allen et al. 20182018; Houle and Cheng 2021; Singh and Agrawal 2023; Grieshop et al. 2025).

In contrast, when there is distinct genetic architecture between sexes or life stages, traits can

evolve towards the same optima under concordant selection, while dimorphisms can evolve

under antagonistic selection. Testing the extent of shared genetic architecture genome-wide is an

important first step to understand the potential for ongoing of conflict between sexes and life

stages.

Expression quantitative trait loci (eQTL) mapping is useful for identifying loci underlying

phenotypic variation or those subject to selection (Kudaravalli et al. 2009; Lee et al. 2014;

Josephs et al. 2015). Local eQTLs, i.e., genetic variants that are significantly associated with the

expression level of a closely linked focal gene, are differentiated from distant eQTLs by a

distance threshold in eQTL mapping studies. Most local regulatory variation acts in *cis* and has

allele-specific effects; we refer to local eQTLs as *cis*-eQTLs or *cis*-regulatory variation. *Cis*-

regulatory variation has a relatively large effect on gene expression, making it easier to map *cis*-

eQTLs in association studies (Josephs et al. 2017; Signor and Nuzhdin 2018). Whether *cis*-

eQTLs affect different sexes or life stages concordantly can be used to infer the extent of shared

genetic architecture between sexes and life stages. For example, a study on eQTLs across human

tissues has shown limited standing variation with sex-specific effects (Genotype × Sex

interaction) in expression, suggesting high potential for sexual conflict under sexually

antagonistic selection (Oliva et al. 2020). Furthermore, selective pressure on eQTLs can be

inferred from their distribution of allele frequencies when compared to the neutral expectation. In

the leaf tissues of *Capsella grandiflora*, *cis*-eQTLs showed excessive rare alleles consistent with

purifying selection (Josephs et al. 2015); whereas in floral tissues of *Mimulus guttatus*, *cis*-

eQTLs exhibited more common than rare alleles (Brown and Kelly 2021). These studies of two

plant species suggest that eQTLs can experience different selective pressures, and that potentially

differential selection can act on genes expressed in different sexes and/or life stages.

We investigated *cis*-regulation of gene expression through *cis*-eQTL mapping in the dioecious,

wind-pollinated and obligately outcrossing annual *Rumex hastatulus* (Polygonaceae). Several

previous findings in *R. hastatulus* indicated the potential for antagonism between sex and life

stages, especially during pollen competition. Sexual dimorphism in phenotypic and life history

traits of this species is likely associated with differential reproductive roles between sexes during

wind pollination, e.g., males are taller and produce more inflorescences during peak flowering to

maximize pollen dispersal while females are taller and have more inflorescences at reproductive

maturity to maximize seed dispersal (Puixeu et al. 2019). Vegetative traits such as leaf

morphology are tightly linked to survival and reproductive success (e.g., Delph et al. 2011;

Scharmann et al. 2021). In *R. hastatulus*, leaf size is positively correlated with plant height in

both sexes, and both leaf number and size are sexually dimorphic (Puixeu et al. 2019). The high

intensity of pollen competition in wind pollinated plants provides an opportunity to test

gametophytic selection during pollen competition (Friedman and Barrett 2009; Field et al. 2012)

and its pleiotropic effects on diploid fitness, e.g., a potential trade-off between pollen success and

diploid offspring fitness. Selection during pollen competition has been shown to affect sex-ratio

bias (Field et al. 2012) and sex chromosome evolution (Sandler et al. 2018) in *R. hastatulus,* e.g.,

female biased sex ratios are likely caused by greater competitive ability of X-bearing pollen

following Y chromosome degeneration (Hough et al. 2014; Crowson et al. 2017). The potential

conflict between sexes and life stages in *R. hastatulus* makes it a promising experimental system

to test the direction of selection on gene expression between sexes and life stages and also to

compare the potential for sexual and life-stage conflict.

We tested differential gene expression between sexes and life stages and mapped *cis*-eQTLs

separately in leaf and pollen tissues to compare their effect sizes and allele frequencies. We

found significantly fewer differentially expressed genes between sexes than between life stages,

and most of the highly sex-biased genes were on the sex chromosomes. There was a greater

overlap in eGenes (i.e., genes with their expression level affected by eQTLs) and eQTLs

between sexes than life stages. Effect sizes of eQTLs were positively correlated between sexes

and life stages, with a much stronger correlation between sexes, indicating more shared genetic

architecture between sexes. Consistent with this result, we found limited Genotype × Sex

interaction in gene expression. Lastly, we found similar selective pressures in eQTLs between

sexes and life stages based on their allele frequency distributions but with no excess of rare

alleles among eQTLs in any tissues when compared to a null distribution. Rare genetic variation

upstream of each gene exhibited both up- and down-regulated gene expression, presumably

reflecting stabilizing selection on gene expression (Kremling et al. 2018; Uzunović et al. 2019).

Results

Differential expression between sexes and life stages

We generated leaf DNA and RNA sequences and pollen RNA sequences from 78 male-female

sibling pairs in a single large population (see Methods). We used male and female leaves to

compare the genetic architecture of gene expression between the sexes and used male leaves and

pollen to compare diploid and haploid life stages, respectively. We performed differential gene

expression analyses to identify sex-biased genes in leaves and life stage-biased genes between

pollen and male leaf tissues (Table S2). Among the 37,659 annotated genes across the genome,

we first filtered for genes with evidence of expression in at least one of the two tissues being

compared, resulting in 19,494 genes in the between-sex comparison and 21,337 genes in the

between-life-stage comparison. In a principal component analysis (PCA) of RNA read counts,

pollen and male leaf samples were separated by PC1 that explained 99% variance both before

and after excluding sex-specific regions on sex chromosomes (Fig S1). Male and female leaf

samples were separated by PC1 which explained 52% of the variance when sex-specific regions

were included but were not separated based on autosomal and pseudoautosomal (PAR) genes

(Fig S1). We identified significantly differentially expressed (DE) genes based on fold change

(FC, the ratio of expression level between two tissues) and the false discovery rate corrected *p*-

value (adjusted *p*), unless stated otherwise, the cutoffs for DE genes are $|\log_2 FC| > 1$ and adjusted

$p < 0.05$. Consistent with the PCA results, there were over 10-fold more DE genes between life

stages (16,649) than between sexes (1,496) (Table S2).

We tested for enrichment of DE genes on sex chromosomes and the overlap between sex-biased

and life stage-biased genes. Sex-biased genes were highly enriched on sex chromosomes (Table

S2), with female-biased genes enriched on the X-specific regions (378/405; Chi-squared test, $p <$

2.2×10^{-16}) and male-biased genes enriched on the Y-specific regions (1,026/1,091; Chi-squared

test, $p < 2.2 \times 10^{-16}$).$^{-16}$) Among 6,702 pollen-biased genes, there was an excess of over-

expression of these genes in male leaves compared to female leaves (30 on autosomes and PAR,

1 on X, 269 on Y) tissue compared to female-biased genes (7 on autosomes and PAR, 63 on X, 3

on Y) (Fisher's exact test, $p = 0.0028$). Although it was a relatively small subset of pollen-based

genes, the larger overlap between male leaf-biased and pollen-biased genes was mostly driven by

the Y-specific regions. This finding implies that selection for higher gametophytic expression in

pollen could have pleiotropic effects on expression in male leaves (and *vice versa*), which could

lead to antagonistic or synergistic pleiotropy for gene expression depending on the direction of

selection on expression between life stages.

A previous study in two *Rumex* species found an enrichment of high pollen expression relative to

leaves on sex chromosomes compared to autosomes, suggesting a role of male gametophytic

selection in Y chromosome evolution (Sandler et al. 2018). With a new PacBio genome

assembly containing X and Y phased assemblies (Sacchi et al. 2025), we attempted to replicate

these results with our gene expression data in *R. hastatulus*. In accord with the earlier results, we

found a significant enrichment of pollen overexpression relative to leaf expression on the Y

chromosome compared to autosomes or the X chromosome (Fig S2, Fisher's exact test, $p =$

0.007 for autosomes, $p = 0.001$ for X) specifically for highly pollen-biased genes ($|\log_2 FC| > 2$,

adjusted $p < 0.05$). Among moderately pollen-biased genes ($|\log_2 FC| > 1$, adjusted $p < 0.05$), we

found a significant enrichment of pollen-biased genes on the Y chromosome only when

compared to the X chromosome (Fig S2, Fisher's exact test, $p = 0.031$ for X, $p > 0.1$ for

autosomes).

eQTLs between sexes and life stages

To test whether *cis*-eQTLs affect expression concordantly between sexes or life stages, we

performed *cis*-eQTL mapping separately in male leaves, female leaves and pollen. For each

gene, we tested the nearby SNPs within 20 kb to the transcription start site for significant

associations between their genotypes and the focal gene's expression level, significant

associations of gene-SNP pairs after false discovery rate corrections would be considered as *cis*-

eQTLs (see Methods). For leaf samples, we mapped *cis*-eQTLs using leaf expression and leaf

genotypes in males and females separately. For pollen samples, we used pollen expression and

male leaf genotypes as they were from the same male individual and shared the same genotypes.

We obtained 4,509,904 and 3,288,995 SNPs on autosomes from 74 female and 69 male leaf

DNA samples, respectively, after removing variants with low minor allele frequency or strong

Hardy–Weinberg deviations. Based on Tracy-Widom tests, we found 5 and 6 significant PCs for

female and male samples explaining 6.53% and 7.7% of genetic variation, respectively (TW

statistic $\geq$ 1.068, $p \leq$ 0.0441 for females; TW statistic $\geq$ 2.288, $p \leq$ 0.00634 for males); we

included the significant PCs as covariates in eQTL mapping.

We identified *cis*-eQTLs and genes whose expression was influenced by eQTLs ("eGenes") in

male leaves, female leaves and pollen (Table 1, Fig S3). We found more shared eGenes and

eQTLs between male and female leaves than between male leaves and pollen (Fig 1a-b). The

number of eQTLs per eGene ranged from 1 to 126 in pollen, 1 to 170 in male leaves, and 1 to

268 in female leaves, with a median of 2 eQTLs per eGene in both male leaves and pollen, and 3

in female leaves. We found eQTLs were located closer to their associated eGenes than the SNPs

tested in all tissues (median distance to the transcription start site: 7718 - 7893 bp for eQTLs vs.

8982 - 9254 bp for tested SNPs). There were similar numbers of eQTLs upstream and

downstream of the transcription start site (Fig S4). When purifying selection reduces the

frequencies of large-effect alleles in expression, there will be a negative correlation between

effect sizes and allele frequencies of eQTLs (Josephs et al. 2015). We found a strong negative

correlation between minor allele frequencies and effect sizes of eQTLs in all tissues when

selecting the most significant eQTL (top eQTL) per eGene (Spearman correlation, ρ = -0.61,

-0.60, -0.66 for male leaves, female leaves, and pollen, respectively; $p < 10^{-16}$) and when

selecting a random eQTL per eGene (ρ = -0.71, -0.72, -0.75 for male leaves, female leaves, and

pollen, respectively; $p < 10^{-16}$) (Fig S5). However, this pattern of negative correlation could also

be caused by confirmation bias.

Table 1. eQTL mapping in male leaves, female leaves and pollen on autosomes. FDR = 0.1.

	Number of samples	Number of genes tested	Number of nearby SNPs tested	Number of eGenes	Number of eQTLs	Number of eQTLs affecting multiple genes	Number of secondary eQTLs
Male leaf	69	14,777	1,272,993	2,421	16,674	486	367
Female leaf	74	14,564	1,687,298	3,442	34,238	905	722
Pollen	69	13,785	1,182,102	1,475	9,456	201	159

Fig 1. Venn diagrams of eGenes (a) and eQTLs (b) between sexes and life stages on autosomes
of *Rumex hastatulus*. FDR = 0.1.

Cis-eQTLs with larger effects end to be closer to the transcription start site (GTEx Consortium et
al. 2017). We found a weak but significant negative correlation between effect sizes of eQTLs
and their distance to the transcription start site in all tissues when selecting the top eQTL
(Spearman correlation, ρ = -0.041, -0.0.049, -0.091 for male leaves, female leaves, and pollen,
respectively; $p < 0.0412$) and when selecting a random eQTL (ρ = -0.067, -0.056, -0.113 for
male leaves, female leaves, and pollen, respectively; $p < 0.001$). In addition to the primary
eQTLs (usually the top eQTLs) in each tissue, for each eGene we examined the independence of
its eQTLs and identified secondary eQTLs (Table 1, see Methods). Secondary eQTLs were
considered as conditionally independent after accounting for the effect of the primary eQTL of
each eGene. We found primary eQTLs were significantly closer to the transcription start site
than secondary eQTLs in female leaf and male leaf tissue (*t*-test, $p = 0.02, 0.009, 0.32$ for female

leaves, male leaves, and pollen, respectively). There were 40 - 43% of secondary eQTLs that had

opposite effects compared to the primary eQTL of the eGene, consisting of 0.7 - 0.9 % of all

eQTLs in each tissue (158 for male leaves, 291 for female leaves, 63 for pollen). The minor

allele frequencies of primary and secondary eQTLs were not significantly different (Mann-

Whitney U-test, $p = 0.12, 0.37, 0.22$ for male leaves, female leaves, and pollen, respectively).

We performed gene ontology enrichment of eGenes in each tissue and examined whether they

showed transcriptional or protein biosynthesis functions. Different tissues showed different

patterns of functional enrichment (Table S3). For example, female leaf tissue showed enrichment

for protein metabolic process (GO:0019538) whereas pollen showed enrichment for mRNA

metabolic process (GO:0016071) and negative regulation of gene expression (GO:0010629).

Additionally, protein deubiquitination (GO:0016579) was enriched in both male leaves and

pollen, and regulation of RNA metabolic process (GO:0051252) was enriched in female leaves

and pollen.

Shared genetic architecture between sexes and life stages

To investigate the extent of shared genetic architecture in expression between sexes and life

stages, we first estimated the correlation in expression level across genes between sexes and life

stages. For comparing sexes, we estimated the correlation in expression between male and

female siblings, which is a phenotypic approximation of the genetic correlation between sexes

(r_{mf}). For comparing life stages, this represents the phenotypic correlation between traits, which

reflects both environmental and genetic variances. We found expression levels were more

positively correlated between sexes than life stages based on all genes and eGenes (Fig 2a-b,

Mann-Whitney U-test, $p < 10^{-16}$ in both comparisons). Even though correlations between life

stages involve the same individual (as opposed to siblings of the opposite sex, for comparing the

sexes), the stronger correlation in expression between sexes, suggests potentially more shared

genetic architecture between sexes than life stages.

Fig 2. Distribution of Pearson correlation coefficients in gene expression between sexes or life

stages in all genes (a) and in eGenes (b) in *Rumex hastatulus*. The dashed line represents the

median of each group: 0.093 (Sex) 0.27 (Life-stage) in a, and 0.14 (Sex) 0.32 (Life-stage) in b.

Numbers of genes: 14992 (Sex) and 16411 (Life-stage) in a, 4493 (Sex) and 3469 (Life-stage) in

b.

Next, we tested whether *cis*-regulatory variation had concordant or discordant effects in gene

expression between sexes and life stages. We filtered for nearby SNPs tested in both sexes or life

stages that were the top eQTL for the eGene in at least one sex or life stage, resulting in 2,420

eQTLs in the sex comparison and 3,077 eQTLs in the life-stage comparison. The majority of

eQTLs showed concordant effects between both sexes and life stages, with their effect sizes

positively correlated (Fig 3a-b). The correlation of eQTL effect sizes was much stronger between

sexes (Spearman correlation, $\rho = 0.72$, $p < 10^{-16}$) than between life stages ($\rho = 0.35$, $p < 10^{-16}$),

suggesting a stronger shared genetic architecture between sexes (Fig 3a-b), as would be predicted

from the phenotypic correlations in Fig 2a-b. There were 170 eQTLs with opposite effects

between sexes, all of which were the top eQTL in one sex but not an eQTL in the other sex (light

orange and light purple dots in Fig 3a). There were 974 eQTLs with opposite effects between life

stages, 19 of which were eQTLs in both life stages (Fig S6). Functional enrichment of eGenes,

with eQTLs showing opposite effects between sexes or life stages, showed an enrichment in

processes relevant to transcription including negative regulation of gene expression

(GO:0010629) and regulation of DNA-templated transcription (GO:0006355), and processes

286   post transcription including regulation of RNA and protein metabolic processes (GO:0051252,
287   GO:0051246) (Table S4).

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Fig 3. Correlation of effect sizes of autosomal SNPs tested between (a) sexes and (b) life stages
in *Rumex hastatulus*. The x and y axes show eQTL effect sizes in different tissues. Black: top
eQTL of the eGene in both sexes or life stages; darker colors: top eQTL in the labelled sex/life
stage, significant but not the top eQTL in the other sex/life stage; lighter colors: top eQTL in the
labelled sex/life stage but not significant in the other sex/life stage. Spearman correlation
coefficients ρ: 0.72 (a), 0.35 (b).

In addition to mapping cis-eQTLs in different tissues separately, we tested for Genotype × Sex
interaction effects on expression more explicitly in a linear model using both male and female
leaf tissues. We obtained 3,684,937 SNPs on autosomes from 143 leaf DNA samples. We found
one significant PC in all leaf samples combined that explained 2% of genetic variation (TW
statistic = 1.328, p = 0.0302) and we included it as a covariate in eQTL mapping. We tested
14,587 genes and 1,083,706 nearby SNPs for the effect of Genotype, Sex, and Genotype × Sex
interaction on expression. After correction for multiple testing (Davis et al. 2016), we found 5
eQTLs showing significant Genotype × Sex interaction (adjusted $p < 0.1$, see Methods), all of
which changed expression of their eGene in the same direction but with different magnitudes
(Fig S7). The small number of eQTLs showing Genotype × Sex is consistent with the previous
result that eQTLs showed strongly correlated effects between sexes (Fig 3a).
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We mapped cis-eQTLs affecting the degree of expression differences between life stages using

16,218 genes and 1,404,801 nearby SNPs. Specifically, we aimed to test the effects of the minor

allele of each SNP on the differences in expression levels between male leaf tissue and pollen.

We found 9,873 eQTLs affecting the expression differences between life stages in 1,564 genes.

There were more eQTLs in which the minor allele increased expression differences (6,173) than

reduced them (3,700), suggesting new mutations (typically represented by the minor alleles)

more often drive the divergence in expression between life stages than constrain it. We examined

whether eQTLs for expression differences between life stages were also identified as eQTLs in

male leaf tissue or pollen separately. We found 767 eQTLs significantly affected leaf expression,

pollen expression, and the differences between them, 735 of which affected leaf and pollen

expression in the same direction, consistent with the concordance in eQTL effect sizes shown in

Fig 3b. Additionally, we found that 1,464 of 1,564 genes, whose expression differences between

life stages were affected by eQTLs, were significantly DE genes between pollen and male leaf

tissue (adjust $p < 0.05$, no FC cutoff). Functional analyses showed rRNA processing

(GO:0006364) and regulation of RNA metabolic processes (GO:0051252) were enriched in

genes with eQTLs affecting life-stage expression differences (Table S5). Lastly, we identified

141 conditionally independent eQTLs affecting life-stage expression differences, 54 of which

had opposite effects compared to the primary eQTL of the same gene.

Selective pressure on eQTLs

We examined the distribution of minor allele frequencies (MAF) of eQTLs to test if selective

pressure differs for eQTLs between sexes or life stages. When compared to the neutral

expectation, an excess of low-frequency variants indicates purifying selection, whereas an excess

of intermediate-frequency variants indicates balancing selection. We kept one eQTL per eGene

to have a set of independent eQTLs for MAF comparisons and repeated the analyses when

keeping the top eQTL and a random eQTL. In all tissues, there were more rare alleles than

common alleles regardless of the eQTL selection method (Fig 4a-f). The median MAFs among

all three tissues were similar, with the highest median MAF in female leaves and lowest median

MAF in male leaves using both methods of eQTL selection (Fig 4). The differences in mean

MAFs between tissues were marginally significant between male and female leaves in top and

random eQTLs (Mann-Whitney *U*-test, $p = 0.041, 0.049$, respectively) and between female

leaves and pollen in top eQTLs (Mann-Whitney *U*-test, $p = 0.049$) (Fig 4).

Fig 4. Distribution of MAFs of eQTLs in male leaves (a, d), female leaves (b, e), pollen (c, f) in

Rumex hastatulus. a-c: top eQTL per eGene, d-e: a randomly selected eQTL per eGene.

Binwidth = 0.01. Dashed lines represent the Median MAF in each plot: 0.1017 (a), 0.1048 (b),

0.1045 (c), 0.0965 (d), 0.0984 (e), 0.0982 (f).

To investigate whether the patterns of more rare than common alleles in eQTLs differed from a

null expectation accounting for sampling and false positives, we compared the MAFs of true

positive eQTLs to a null distribution in each tissue (Fig 5a-c). We generated the null distributions

of MAFs using 'false-positive' eQTLs from permuted data by breaking the true assignment of

individuals and re-assigning their expression phenotypes. We then used the same procedure to

identify false-positive eQTLs from permuted data and true positive eQTLs from observed data

(see Methods). In all tissues we found an excess of rare alleles (MAF between 0.05 and 0.1) in

the permuted data compared to our observed data, with a small overlap in the proportions of rare

alleles in pollen (Fig 5a-c), suggesting that eQTLs do not appear to be less common than would

be expected under a null model.

Fig 5. Distribution of MAFs of eQTLs compared to a null distribution in male leaves (a), female leaves (b) and pollen (c) in *Rumex hastatulus*. Black dots: true positive eQTLs (observed data), grey dots: false positive eQTLs (permuted data).

Studies have found more *cis*-regulatory variation in unbiased and moderately biased than strongly biased genes between the sexes of *Drosophila melanogaster*, suggesting potential sexual conflict in regulatory variation (Puixeu et al. 2023; but see Mishra et al. 2024). We tested signals of potential antagonistic selection between sexes or life stages. We first compared MAFs of eQTLs shared between life stages with those that were life-stage specific. We found shared eQTLs had significantly higher MAFs than specific eQTLs (Mann-Whitney *U*-test, $p < 10^{-7}$), with median MAFs of 0.143 and 0.093, respectively. This result was not confirmed by a comparison to a null distribution due to a lack of shared false positive eQTLs between life stages. We also tested signatures of selection on eGenes that were shared between sexes or life stages using neutral diversity statistics. We predicted that shared eGenes would have higher π and Tajima's *D* than specific eGenes, due to the greater potential for conflict in shared eGenes. We found that shared eGenes between sexes had significantly higher Tajima's *D* (Kruskal-Wallis test, $p < 10^{-5}$) but not significantly higher π (Kruskal-Wallis test, $p = 0.5383$) than male- or female-specific eGenes. There were no significant differences in π or Tajima's *D* among shared and specific eGenes in either life stage (ANOVA test, $p = 0.611, 0.157$, respectively). Additionally, we tested the signature of selection on eGenes whose expression differences between life stages were affected by eQTLs and found these eGenes had significantly higher π

and Tajima's *D* than eGenes not significant for expression differences (*t*-test, *p* = 0.00013,

0.00058, respectively).

Burden of rare alleles on gene expression

While our comparisons of allele frequencies of eQTLs to the null distribution suggest a

deficiency of rare variants rather than a signal of purifying selection on variants affecting gene

expression, rare variants are excluded in eQTL mapping due to the lack of power to detect

associations. To address this limitation, we also performed burden of rare allele tests that assess

signatures of stabilizing selection in gene expression (Zhao et al. 2016; Kremling et al. 2018;

Uzunović et al. 2019). The burden of rare allele test evaluates the shape of the distribution of

total counts of rare alleles across ranked bins of varying expression levels. If rare alleles increase

or decrease expression level, individuals with highest or lowest expression ranks will show a

higher number of rare alleles (a parabolic shape), as would be expected under stabilizing

selection against extreme expression. In *Capsella grandiflora*, rare SNPs are equally probable to

increase and decrease expression (Uzunović et al. 2019); whereas in maize, rare SNPs upstream

of genes are more likely to decrease expression (Kremling et al. 2018). We ranked individuals'

expression levels for each gene and counted the number of singletons (i.e., variants that only

appear once across all individuals) 5kb upstream of the gene across all genes for each expression

rank bin and plotted their relationship (Fig 6). Our results showed that in male and female leaves,

rare alleles with both up- and down-regulated expression occurred (Fig 6a-b), similar to the

results in *Capsella grandiflora* (Uzunović et al. 2019). There was a slightly stronger effect of

rare alleles in increasing than decreasing expression indicated by outliers in the highest rank

bins, but overall, the parabolic shape was symmetrical (Fig 6a-b). In pollen we did not see the

same effects as in leaf tissues, there was an absence of the parabolic relationship (Fig 6c).

Fig 6. Relationship between rare allele count and gene expression rank bin in male leaves (a),

female leaves (b) and pollen (c) in *Rumex hastatulus*. Smooth lines show quadratic regression in

a and b and linear regression in c. a. adjusted R^2 = 0.5288, p = 6.149×10^{-12}. b. adjusted R^2 =

0.5484, p = 2.067×10^{-13}. c. adjusted R^2 = 0.3481, p = 5.756×10^{-8}. Lowest rank means lowest

expression and highest rank means highest expression.

Discussion

In this study we mapped *cis*-eQTLs in leaf and pollen tissues in the dioecious plant *R. hastatulus*

to investigate the potential for conflict between sexes and life stages, based on shared genetic

architecture. We investigated the overlap of eQTLs between sexes and life stages and examined

their effect sizes and allele frequencies. We discovered a much larger overlap in eGenes and

eQTLs between sexes than between life stages. For SNPs tested in both sexes or life stages, there

was a stronger correlation of effect sizes between sexes suggesting a more shared genetic

architecture between sexes than life stages. There were more minor alleles of eQTLs driving than

constraining divergent expression between life stages. Among the eQTLs shared between life

stages and affecting their expression differences, most minor alleles changed expression in the

same direction with different magnitudes, increasing the degree of divergent expression. MAFs

of eQTLs in all tissues exhibited similar distributions with a larger proportion of rare alleles than

common alleles, but this pattern did not reflect an excess of rare variants when compared to a

null distribution. Investigation of the burden of rare allele on genotypes with more extreme gene

expression suggested that rare variants both up- and down-regulated expression. Below we

discuss the implications of our results on the extent of a shared genetic architecture between sex

and life stages and also the use of eQTL mapping in testing evolutionary forces shaping *cis-*

regulatory variation.

Potential for conflict between sexes and life stages

With the potential for both sexual and life-stage conflict based on theory (Kidwell et al. 1977;

Immler et al. 2012; Peters and Weis 2018), key open questions remain on whether there are more

opportunities for conflict between sexes or life stages, and whether sexual and life-stage conflict

is still an ongoing process or has already become resolved. We investigated these questions using

cis-regulatory variation which has a strong effect on gene expression. Our results consistently

suggested significantly greater shared genetic architecture between sexes than life stages, thus

more potential for ongoing sexual conflict. Furthermore, our results indicated that life-stage

conflict is more resolved compared to sexual conflict. These findings are consistent with

previous work suggesting considerable scope for ongoing sexual conflict based on intersexual

genetic covariances in expression (Allen et al. 20182018; Houle and Cheng 2021; Singh and

Agrawal 2023; Grieshop et al. 2025).

It is also worth mentioning that standing variation in gene regulation might have more sex-

differential effects in reproductive tissues such as in flowers compared to leaves. Future studies

could benefit from a more diverse sampling of both vegetative and reproductive tissues (e.g.,

comparing pollen and ovule or shared floral tissues) than we used in this study. The alternating

life cycle of diploid and haploid life stages is shared among all land plants, allowing adaptation

to varying environments. While sexual reproduction is an ancient attribute of eukaryotic

organisms, dioecy in flowering plants has more recently emerged from hermaphroditic ancestors

in most lineages (Bawa 1980), and there probably has not been enough time to break down

intersexual genetic correlations. Our conclusion that there is more potential for sexual than life-

stage conflict in dioecious flowering plants should be robust in terms of tissue sampling due to

the relatively recent evolution of separate sexes compared to the fundamental feature of the

haploid-diploid alternating life cycle. In dioecious plants such as *R. hastatulus*, it is likely that

there has been a greater amount of time to resolve conflicts between life stages than sexes, where

sexual conflict between females and males may still be ongoing. Direct assessments of

antagonistic selection between sexes and life stages should provide a more complete picture of

the evolution of these two types of conflict.

While our results suggest the potential for unresolved sexual conflict in gene expression on

autosomes, sex chromosomes have important roles in the evolution of dioecy (Charlesworth et

al. 2005) and can facilitate the evolution of sexual dimorphism (Rice 1984; Zemp et al. 2016).

The vast majority of identified sex-biased genes were found to be sex-linked, suggesting a

potential role for sex chromosomes in resolving sexual antagonism. Plants are useful systems for

comparing opportunities for sexual and life-stage conflict (Moore and Pannell 2011; Beaudry et

al. 2020). Whether there is more shared genetic architecture between sexes and life stages in

plant lineages with different reproductive systems or sex chromosome systems (presence and

absence or age of sex chromosomes) is therefore worth further investigation. Also, whether there

are differences in sexual and life-stage conflict in plants with contrasting sexual systems

(hermaphroditic vs. dioecious) or different types of life cycles (predominantly diploid vs.

haploid) are also promising topics for future research.

With a weak positive correlation of eQTL effect sizes between life stages there is still potential,

albeit weaker, for ongoing life-stage conflict. We found that genes on the Y chromosome with

higher expression in pollen compared to leaves also tended to be male-biased in leaves,

suggesting the possibility of strong selection in pollen, possibly driving up leaf expression in an

antagonistic fashion. We examined signatures of conflict on eGenes using diversity statistics. We

expected eQTLs with concordant effects between sexes or life stages to experience stronger

conflict than those with discordant effects or those exclusive to one sex or life stage. We found

that shared eGenes had higher Tajima's D than sex-specific eGenes. In contrast to our prediction,

eGenes with eQTLs affecting their expression differences between life stages had significantly

higher π and Tajima's D than eGenes not significant for expression differences; however, this

finding might result from an ascertainment bias, as it is more likely to have higher power to

detect interactions when diversity is higher. Overall, there was no indication of greater

antagonistic selection on eQTLs with shared genetic architecture between the sexes and life

stages.

Our previous study tested the genomic signature of intra-locus conflict between life stages in $R.$

hastatulus using gene expression but did not find support for a genome-wide signal (Yuan et al.

2025). Conditions for generating balancing selection due to conflict are limited to single large-

effect loci (Kidwell et al. 1977). Detecting balancing selection due to conflict using genomic data

remains challenging, especially when polygenic traits are involved (Bitarello et al. 2023;

Flintham et al. 2025; Ruzicka et al. 2025). While variation in gene expression can underlie

important phenotypic variation, it is worth noting that the relationship between expression

variation and morphological variation can be complicated and different across tissues. Clearly,

there is more to be understood about the relationship among gene expression, phenotypic traits

and fitness. For example, the genetic basis of the traits under antagonistic selection needs to be

considered when testing for signals of conflict (Rowe et al. 2018). Future studies with more

functional information (e.g., on alleles beneficial for pollen competition), combined with

previously identified candidate genes under balancing selection (Yuan et al. 2025) should help to

uncover the genetic basis of life-stage conflict in *R. hastatulus*.

Selective pressure on cis-regulatory variation

Estimating selective pressures in regulatory variation using allele frequencies has resulted in

mixed results supporting contrasting hypotheses about the type of selection on *cis*-eQTLs

(Josephs et al. 2015; Brown and Kelly 2021). Our results indicated more rare than common

alleles among cis-eQTLs in all tissues. However, in contrast to our prediction and previous

findings in *Capsella grandiflora* (Josephs et al. 2015), we found a non-significantly higher

proportion of rare alleles in the null distribution than our observed data, suggesting a genome-

wide signature of purifying selection was unlikely. Assuming the null distribution from genome-

wide SNPs reflects neutrality, the slight deficiency of rare alleles could potentially be caused by

antagonistic selection or other factors. However, the genome-wide null distribution likely

includes a sampling of variants subject to purifying selection, so it is also possible that eQTLs

experience relaxed purifying selection. Interestingly, our results are intermediate between those

reported in *Capsella grandiflora* and the *cis*-eQTLs in *Mimulus* floral tissues, which showed a

higher proportion of common than rare alleles (Brown and Kelly 2021).

While our *cis*-eQTL mapping removed rare variants and only included variants with large

enough effect to be detectable in this study, our burden of rare allele tests provided a more

powerful assessment of selective pressure on genetic variation affecting gene expression than

comparing genome-wide allele frequency spectra of eQTLs to a null distribution. We found a

signal of stabilizing selection on gene expression in leaves using this approach, with an excess of

rare allele burdens at both extremes of expression rank, suggesting selection on optimal

expression level (Hodgins-Davis et al. 2015). In contrast, we observed no clear signal of

stabilizing selection on gene expression in pollen. This may indicate that pollen expression is

generally subject to weaker selection in *R. hastatulus*, a conclusion that is supported by our

recent results suggesting relaxed purifying selection on pollen-biased genes (Yuan et al. 2025).

Future studies should benefit from examining the correlation between effect sizes and MAFs,

while controlling for confirmation bias using allele-specific eQTLs (Josephs et al. 2015) and

examining *trans*-eQTLs as they have been found in other species to be subject to stronger

constraint than *cis*-acting variation (Josephs et al. 2020).

In conclusion, our results indicate a greater shared genetic architecture in gene expression

between the sexes than between the haploid and diploid phase of the lifecycle, and evidence for

stabilizing selection on gene expression in leaves but not pollen. While these results imply the

potential for a greater constraint in response to antagonistic selection between the sexes because

of genetic architecture, the extent of standing variation in sexual antagonism remains difficult to

ascertain from our results alone. There are limitations in the application of the site frequency

spectrum of eQTLs for testing ongoing antagonistic selection and future work using more direct

mapping of fitness effects of genetic variants (e.g., Ruzicka et al. 2019; Delph et al. 2022) will be

important to test this further.

Methods

Plant materials

We described the details of plant materials and sequencing in Yuan et al. (2025); here we

provide a brief summary and additional relevant information. After generating seedlings using

open-pollinated seeds collected from a population in Rosebud, Texas, US (Pickup and Barrett

2013), we paired one female and male individual randomly at the time of flowering for crossing

and collected seeds to generate F_1 plants. We planted and retained multiple individuals per

family for 78 F_1 families to ensure we had one male-female full sibling pair per family for tissue

collection. We collected young leaf tissue from each male-female full-sibling pair after flowering

for both RNA and DNA sequencing and collected mature pollen grains from males for RNA

sequencing. We described the DNA and RNA isolation protocols in Yuan et al. (2025). The

DNA samples were sequenced at a depth of 10-15X. Raw sequences of male leaf RNA and

pollen RNA were described in Yuan et al. (2025), Initial sample sizes for DNA samples and

female leaf RNA samples are presented in Table S1.

DNA Seq data and variant calling

We used a phased PacBio genome assembly consisting of four autosomes, X-specific, Y-specific

and pseudoautosomal regions for our analyses (Sacchi et al. 2025). We mapped the DNA reads

to the genome assembly and added read groups using bwa-mem2 (Vasimuddin et al. 2019). We

sorted the BAM, marked PCR duplicates and indexed the final BAM using SAMTools (Danecek

et al. 2021). We called variants in parallel on 2 Mb non-overlapping contigs of each chromosome

for all samples using BCFtools mpileup (Danecek et al. 2021), then concatenated the VCFs of

contigs for each chromosome. We removed one male sample (24fM) due to low genomic

coverage and two samples due to incorrect sex labeling (35aM, 40aF), and only kept samples

with both DNA and RNA sequences from the same individual. For males, we only kept samples

with both leaf and pollen RNA sequences from the same individual. Our sample sizes for VCF

filtering were 74 for female leaves, 73 for male leaves, making a total of 147 leaf tissue samples.

We performed SNP filtering as follows for female leaf, male leaf and all leaf samples combined

separately using VCFtools (Danecek et al. 2011). We kept SNPs with QUAL > 30, a mean depth

between 5 and 20, a genotype quality per sample > 30 otherwise marked as missing, and finally a

missingness < 20%. For female samples, we used the same filtering criteria for autosomes, PAR

and X-specific regions. The numbers of autosomal SNPs were 64,988,762 in male leaf,

66,828,708 in female leaf, and 66,341,762 in all leaf samples combined. The numbers of SNPs

on X-specific regions and PAR in females were 7,745,941 and 2,164,214, respectively.

Additionally, we filtered for invariant sites on autosomes with a mean depth between 5 and 20

and a missingness < 20% for all leaf samples combined.

We removed SNPs with a minor allele frequency lower than 5% or with strong Hardy–Weinberg

deviations ($p < 10^{-6}$) on autosomes using Plink (Chang et al. 2015) to test for population structure

and for the subsequent eQTL mapping. We removed four male samples (7bM, 27eM, 53bM,

5aM) from subsequent analyses for being outliers in principal component analyses in Plink

(Chang et al. 2015). Our final sample sizes were 74 for female leaves, 69 for male leaves,

making a total of 143 leaf samples. After the filtering using Plink, the numbers of SNPs on

autosomes were 3,288,995 in male leaves, 4,509,904 in female leaves, and 3,684,937 in all leaf

samples combined; the numbers of SNPs on X-specific regions and PAR in females were

769,059 and 96,911, respectively.

RNA Seq data and expression analyses

We mapped the RNA reads to our genome assembly in a two-pass mode, sorted the BAM files

by coordinates, added read groups using STAR (Dobin et al. 2013), and indexed the output BAM

files using SAMTools (Danecek et al. 2021). We generated read counts for each gene using

featureCount (Liao et al. 2014). We only kept genes with evidence of expression for our

subsequent analyses, i.e., genes with a mean raw read count ≥ 5 in a specific tissue, or in at least

one tissue for analyses involving both sexes or life stages. We identified sex-biased genes in leaf

tissues and life-stage-biased genes by comparing pollen and male leaf tissues using DESeq2

(Love et al. 2014). The cutoffs for significant differentially expressed (DE) genes were

Benjamini-Hochberg adjusted $p < 0.05$ and $|\log_2 FC| > 1$ unless stated otherwise.

We prepared the expression phenotype data for each tissue separately and for all leaf samples

combined for eQTL mapping. We normalized raw read counts by sequencing depth using

DESeq2 (Love et al. 2014) and performed quantile normalization using the qqnorm function in R

(R Core Team 2022). Additionally, we calculated the difference of normalized read counts in

pollen and male leaves (male leaf minus pollen) for each gene and performed quantile

normalization of its absolute value using the qqnorm function in R (R Core Team 2022).

Correlation in gene expression

To characterize the correlation in expression across life stages or sexes, we used Pearson

correlations and the final normalized read counts as expression level as described above. For

male leaves and pollen, we calculated the correlation of a given gene's expression level in each

tissue using 69 male individuals and repeated for 16,411 autosomal genes that had evidence of

expression (as described above) to generate a distribution of correlations. These correlations are

the same as any phenotypic correlation in behavioral or morphological traits, but here are for

gene expression (Stinchcombe and Kelly 2025). To estimate the across-sex correlation in

expression, we took advantage of the sib-structure of our design and the fact that we had male

and female sibling pairs. We used the expression level of a gene in a male sample and its female

sibling as a pair of observations, repeated for 64 sibling pairs in our design, to estimate the

correlation in expression across siblings for a given gene. We then repeated this for 14,992 genes

with evidence of expression in the samples to generate a distribution of across-sex correlation in

expression. Note that because we only had a single male and female sample per family, rather

than replicates, this is a phenotypic approximation of the across-sex genetic correlation (r_{mf}),

rather than a genetic correlation. We repeated the analyses for genes regulated by eQTLs

(eGenes, see below) in at least one life stage or sex following the same steps.

eQTL mapping

We performed *cis*-eQTL mapping on autosomes separately for male leaves, female leaves, and

pollen tissue. For female leaves, we repeated eQTL mapping on X and PAR using the same

approach as the autosomes. For male samples, we performed eQTL mapping using the difference

in leaf and pollen expression levels as phenotypes in the same way as in leaves or pollen

separately. To control for genetic relatedness, we performed LD pruning in Plink (Chang et al.

2015) and identified genetic principal components (PC) using EIGENSOFT smartpca (Patterson

et al. 2006; Price et al. 2006). The significance of each PC was determined by the Tracy-Widom

test (Patterson et al. 2006; Sztepanacz and Blows 2017). We included the significant PCs ($p <$

0.05) as covariates in eQTL mapping.

We mapped *cis*-eQTL using tensorQTL (Taylor-Weiner et al. 2019) following its guidelines, and

tested pre linkage-pruning SNPs within a 20 kb window to the transcription start site for each

gene. We performed adaptive permutations to calculate empirical and beta-approximated

empirical *p*-values for each gene (Ongen et al. 2016), and generated nominal *p*-values for all

SNP-gene pairs. We calculated the Storey *q*-value and the nominal *p*-value threshold for

significant associations based on the beta-approximated empirical *p*-value for each gene using a

false discovery rate (FDR) of 0.1 (Benjamini and Hochberg 1995; Storey 2002). We filtered for

genes that had *q*-value < 0.1 and at least one eQTL as our eGenes. We filtered for SNPs with a

nominal *p*-value smaller than the nominal *p*-value threshold of its eGene as our eQTLs. The

minimum *p*-value threshold is 0.0318 for male leaves, 0.0503 for female leaves, and 0.0166 for

pollen. We identified conditionally independent eQTLs for eGenes using a forward-backward

stepwise regression model in tensorQTL (GTEx Consortium et al. 2017). We defined primary

eQTLs as the top ranked eQTL for each eGene, and any additionally ranked eQTLs as secondary

or conditionally independent eQTLs. The effect size of an eQTL was defined as the slope in the

linear regression model from tensorQTL. In the analyses of eQTLs for differences in expression

levels between life stages, effects of the minor allele were tested rather than alternative allele of

each SNP.

We kept one eQTL for every eGene, either the most significant (top) eQTL or a randomly

selected eQTL when comparing minor allele frequencies (MAF) and when testing the

relationship between effect size and the distance to transcription start site of eQTLs. We

removed eQTLs and eGenes when an eQTL affected multiple eGenes when comparing MAFs.

We performed gene ontology enrichment of eGenes using topGO (Alexa and Rahnenfuhrer

2023), significant GO terms were selected using a *p*-value cutoff of 0.05 based on Fisher's exact

tests.

We ran tensorQTL on all 143 leaf samples to test the linear model: Expression ~ Genotype + Sex

+ Genotype × Sex. We kept the top association for each gene based on the interaction term (-best

only), and calculated multiple-testing corrected (Davis et al. 2016) and Benjamini-Hochberg

adjusted *p*-values (pval_adj_bh) following the recommendations from tensorQTL. The cutoff for

eQTLs showing significant Genotype × Sex is pval_adj_bh < 0.1.

Null distributions of eQTL MAFs

To generate a null distribution for MAFs of eQTLs in each tissue, we performed permutations by

randomly re-assigning sample ID's in the expression phenotype file. We performed 1000

permutations in both females and males. For female leaves, we performed the same permutations

on X and PAR as the autosomes. For male samples, we performed permutations the same way in

male leaf and pollen phenotypes and identified the shared and specific eQTLs between male

leaves and pollen in each permutation. We identified false-positive eQTLs using the same *p*-

value thresholds from the previous analyses on our observed data. We removed eGenes with

more than 10 eQTLs, randomly selected an eQTL from each eGene, and removed eQTLs

affecting multiple eGenes. We repeated the same procedure of calculating MAF using true

positive eQTLs. The proportions of false positive eGenes compared to true positive eGenes were

0.059 in male leaves, 0.105 in female leaves, and 0.0318 in pollen, based on the median number

of false positive eGenes in 1000 permutations.

Diversity statistics

We used the script codingSiteTypes.py

(https://github.com/simonhmartin/genomics_general/blob/master/codingSiteTypes.py, accessed

in 2020) to extract 4-fold degenerate site for calculating neutral diversity statistics. We generated

4-fold VCFs including both variant and invariant sites using all leaf samples combined. We used

pixy (Korunes and Samuk 2021; Bailey et al. 2025) to calculate nucleotide diversity (π) and

Tajima's *D* for all autosomal genes. We only kept genes with at least 50 sites in the subsequent

analyses of π and Tajima's *D*. We removed genes if they were associated with an eQTL that

affected multiple eGenes.

Burden of rare allele test

We performed the 'burden of rare allele' test separately for male leaves, female leaves and pollen

using the methods described in Zhao et al. (2016). We counted the number of singletons in the

5kb upstream window from the transcription start site for each gene and each individual. We

ranked the individuals for each gene based on their expression level, for each rank we summed

the number of local singletons from all genes regardless of their individual identity. Finally, we

plotted the sum of rare alleles against rank bins (bin size = 1) and performed quadratic or linear

regression to assess relationship between rare allele counts and gene expression ranks.

Data availability

702 Raw sequencing reads are available through the NCBI SRA database under BioProject

703 PRJNA744278. Scripts used in this study are available at

704 https://github.com/SIWLab/Rumex_eQTL.

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