Short Title: Genetic Architecture of Gene Expression in Tomato

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Title: eQTL in a Precisely Defined Tomato Introgression Population Reveal Genetic Regulation of Gene Expression Patterns Related to Physiological and Developmental Pathways

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Summary: Genetical genomics approach in tomato identified genetic hotspots that regulate gene expression patterns relating to diverse biological processes such as plant development, photosynthesis and defense.

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Abstract

Variation in gene expression, in addition to sequence polymorphisms, is known to influence developmental, physiological and metabolic traits in plants. Genetical genomics approaches on genetic mapping populations have facilitated the identification of expression Quantitative Trait Loci (eQTL), the genetic determinants of variation in gene expression patterns. We used an introgression population developed from the wild desert-adapted *Solanum pennellii* and domesticated tomato *Solanum lycopersicum* to identify the genetic basis of transcript level variation. We established the effect of each introgression on the transcriptome through differential gene expression analysis, and identified ~7,200 eQTL regulating the expression of 5,300 genes. Barnes-Hut *t*-distributed stochastic neighbor embedding clustering identified 42 modules revealing novel associations between gene expression patterns and biological processes. The results showed a complex genetic architecture of global gene expression pattern in tomato. Several genetic hotspots regulating a large number of gene expression patterns relating to diverse biological processes such as plant defense and photosynthesis were identified. We identified important eQTL regulating gene expression patterns related to leaf number and complexity, and hypocotyl length. Genes associated with leaf development showed an inverse correlation with photosynthetic gene expression but their regulation was dispersed across the genome. This is the first comprehensive insight into the global regulation of transcript abundance in tomato and its influence on plant

phenotypes, which sets the stage for identifying gene/s underlying these regulatory loci.

Introduction

The genetic basis of many qualitative and quantitative phenotypic differences in plants has been associated with sequence polymorphisms and the corresponding changes in gene function. However, differences in the levels of gene expression, without underlying changes in coding sequences, also significantly influence plant phenotypes. Closely related plant species often have little coding sequence divergence, nonetheless they often develop unique physiological, metabolic, and developmental characteristics indicating that patterns of gene expression are important in species-level phenotypic variation (Kliebenstein, 2009; Koenig et al., 2013). Phenotypic differences attributed to variations in gene expression patterns have been found to influence disease resistance, insect resistance, phosphate sensing, flowering time, circadian rhythm, and plant development (Kroymann et al., 2003; Werner et al., 2005; Clark et al., 2006; Zhang et al., 2006; Svistoonoff et al., 2007; Chen et al., 2010; Hammond et al., 2011).

Global gene expression changes across defined genetic backgrounds have been used to identify expression Quantitative Trait Loci (eQTL) through genetical genomics approaches (Jansen and Nap, 2001; Kliebenstein, 2009; Druka et al., 2010; Chitwood and Sinha, 2013). An eQTL is a chromosomal

region that drives variation in gene expression patterns (i.e., transcript abundance) between individuals of a genetic mapping population and can be treated as a heritable quantitative trait (Brem et al., 2002; Kliebenstein, 2009; Cubillos et al., 2012). Recent advances in next-generation sequencing have enabled high-throughput genotyping and transcript abundance estimation to provide direct readouts of the regulatory changes in mapping populations, allowing identification of thousands of eQTL in a single experiment (Pickrell et al., 2010; Chitwood and Sinha, 2013; Battle et al., 2015). Global eQTL studies in animals, fungi, and plants have provided genetic insights into the transcriptional regulation of these organisms (Brem and Kruglyak, 2005; Keurentjes et al., 2007; West et al., 2007; Schadt et al., 2008; Hammond et al., 2011; Holloway et al., 2011; Zhang et al., 2011; Cubillos et al., 2012).

Depending upon the proximity to the gene being regulated, eQTL can be classified into two groups: *cis*-eQTL when the physical location of an eQTL coincides with the location of the regulated gene, and *trans*-eQTL when an eQTL is located at a different position from the gene being regulated (Kliebenstein, 2009). eQTL studies with the model plant Arabidopsis underlined the significance and contributions of *cis*- and *trans*-eQTL (DeCook et al., 2006; West et al., 2007; Holloway and Li, 2010). *Cis*-eQTL have a significant effect on local expression levels, whereas *trans*-eQTL often have global influences on gene regulation. Individual genes can have multiple *trans*-eQTL contributing to the regulation of their expression pattern. Identification of *trans*-acting eQTL hotspots, defined as regions affecting the expression of a significantly larger number of genes than

132 expected, have been found in many eQTL studies. Genes underlying an eQTL
133 hotspot could be master transcription factors controlling the expression of a suite
134 of genes that act in the same biological process or pathway. For example, eQTL
135 hotspots in Arabidopsis co-locate with the *ERECTA* locus, which has been
136 shown to pleiotropically influence many traits including those regulating
137 morphology (Keurentjes et al., 2007). In addition, the eQTL identified using
138 pathogen challenged tissues in barley were enriched for genes related to
139 pathogen response (Chen et al., 2010; Druka et al., 2010). Similarly the rice *sub1*
140 locus, which regulates submergence tolerance, controls the activity of an
141 ethylene response factor with significant *trans* effects (Fukao et al., 2006; Xu et
142 al., 2006). Thus eQTL analyses have the potential to reveal a genome-wide view
143 of the complex genetic architecture of gene expression regulation, the underlying
144 gene regulatory networks, and may also identify master transcriptional regulators.
145 Cultivated tomatoes, along with their wild-relatives, harbor broad genetic
146 diversity and large phenotypic variability (Moyle, 2008; Ranjan et al., 2012).
147 Wide interspecific crosses bring together divergent genomes and hybridization of
148 such diverse genotytpes leads to extensive gene expression alterations
149 compared to either parent. Gene expression in hybrids often deviates from purely
150 additive effects and may contribute to hybrid vigor and in nature can act as a
151 source of variation for selection to act upon (Hegarty et al., 2008). Introgression
152 lines (ILs), developed by crosses between wild-relatives and the cultivated
153 tomato to bring discrete wild-relative genomic segments into the cultivated
154 background, have proved to be a useful genetic resource for genomics and

molecular breeding studies. One such highly characterized introgression population was developed from the wild desert-adapted species *Solanum pennellii* and domesticated *Solanum lycopersicum* cv. M82 (Eshed and Zamir, 1995; Liu and Zamir, 1999). These two species exhibit large phenotypic differences for both developmental and metabolic traits. This IL population has been successfully used to map numerous QTL for metabolites, enzymatic activity, yield, fitness traits, and developmental features, such as leaf shape, size, and complexity (Frary et al., 2000; Holtan and Hake, 2003; Fridman et al., 2004; Chitwood et al., 2013; Muir et al., 2014). Though these studies led to fine mapping of candidate genes underlying identified QTL, phenotypic QTL mapping does not provide insight into the molecular regulation and gene networks underlying a trait. Comparative transcriptomics using cultivated and wild species enables identification of transcript abundance variation potentially underlying trait differences, such as salt tolerance, between species (Koenig et al., 2013). However, the genetic regulators of these transcriptional differences between the species still need to be elucidated. Therefore, we used a genetical genomics approach to identify the genetic basis of transcript level variation in tomato using the *S. pennellii* introgression lines.

Using both genomic DNA and RNAseq reads we recently pinpointed the exact gene content harbored in the introgression regions for the *S. pennellii* ILs and identified more than a thousand QTL underlying plant developmental traits, including leaf traits (Chitwood et al., 2013). Here we report on a comprehensive transcriptome profile of the ILs, a comparison between the gene expression

patterns of the ILs and the cultivated M82 background (differential gene expression – DE), as well as a global eQTL analysis to identify patterns of genetic regulation of transcript abundance in the tomato shoot apex. We have identified more than 7,200 *cis*- and *trans*-eQTL in total, which regulate the expression patterns of 5,300 genes in tomato. Additional analyses using Barnes-Hut *t*-distributed stochastic neighbor embedding (BH-SNE) (van der Maaten, 2013) identified 42 modules revealing novel associations between gene expression patterns and biological processes. The gene expression patterns under strong genetic regulation are related to plant defense, photosynthesis, and plant developmental traits. We also report important eQTL regulating gene expression pattern associated with leaf number, complexity, and hypocotyl length phenotypes.

Results and Discussion

Transcriptome Profiling of Introgression Lines

RNAseq reads obtained from the tomato shoot apex with developing leaves and hypocotyl were used to identify differentially expressed (DE) genes between each *S. pennellii* IL and the cultivated M82 (Supplemental Dataset 1). The total number of genes differentially expressed for each IL both in *cis* (in this population reflecting “local” level regulation either from within a gene itself or other genes in the introgression) and *trans*, along with the number of genes in the introgression regions, are presented in Figure 1 and Supplemental Table I. There was a strong correlation between the number of genes in the introgression

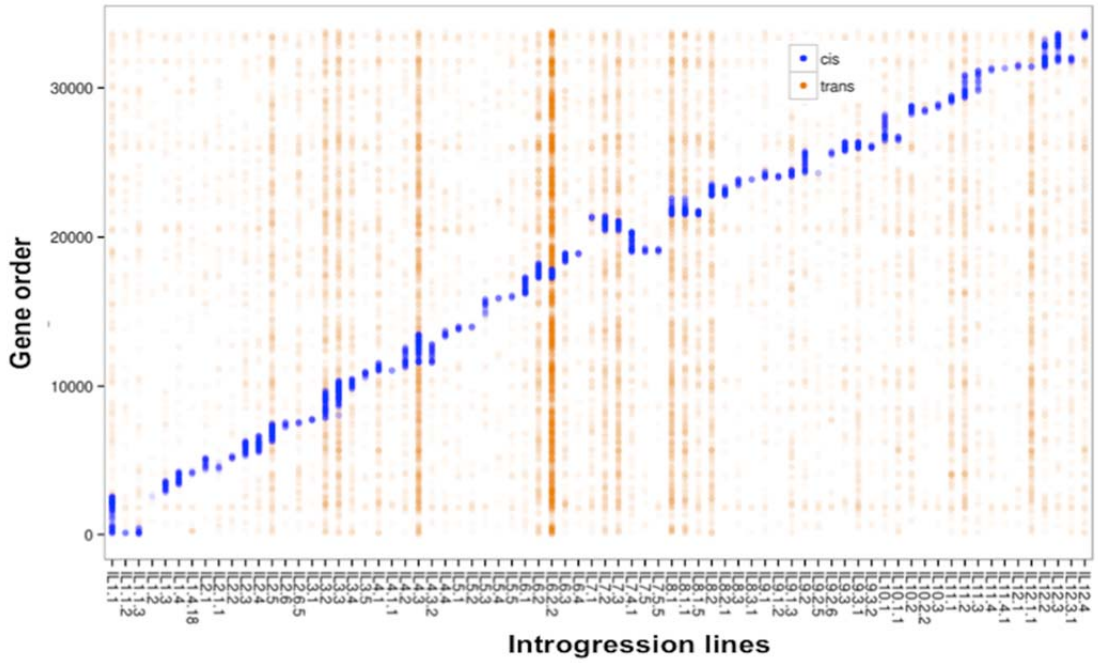

Figure 1. Transcriptome profile of the tomato introgression lines. Differentially expressed genes for the ILs compared to cultivated parent M82. Y-axis shows all the tomato genes starting from the first gene on chromosome 1 to the last gene on chromosome 12, and X-axis depicts the individual ILs. Genes differentially expressed within the introgression regions (in *cis*) are shown as blue points and differentially expressed genes in *trans* (outside) the introgression region are shown as orange points.

regions and the number of DE genes in *cis* (Supplemental Figure S1A). In contrast, the number of DE genes in *trans* was poorly correlated with introgression size (Supplemental Figure S1B). ILs showing higher total number of DE genes, such as IL6.2.2 and IL4.3, showed regulation of most of the DE genes in *trans* (Figure 1, Supplemental Table I, Supplemental Figure S2). IL12.1.1, despite having one of the smallest introgressions, showed 96% of ~500 DE genes regulated in *trans* (Supplemental Table I, Supplemental Figure S2). In contrast, IL1.1 and IL12.3, the ILs with highest number of genes in the introgression regions, showed smaller numbers of total and *trans* DE genes (Figure 1, Supplemental Table I, Supplemental Figure S2). Together these examples suggest that specific loci and not the introgression size determine gene regulation in *trans*. For example, *S. pennellii* chromosomal regions introgressed

213 in IL6.2.2 and IL12.1.1 have stronger genetic influence on global transcript
214 abundance than the regions introgressed in IL1.1 and IL2.3. This could, in part,
215 be due to the presence of genes encoding key transcription factors or
216 developmental regulators in these regions with strong influence on gene
217 expression pattern as is seen in the *ERECTA* containing genomic region in
218 Arabidopsis (Keurentjes et al., 2007). A total of 7,943 unique tomato genes were
219 DE between the ILs and cv. M82, representing approximately one third of the
220 ~21,000 genes with sufficient sequencing depth to allow DE analysis. This
221 suggests that in addition to protein coding differences, transcriptional regulation
222 of less than one third of all genes accounts for most of the phenotypic and trait
223 differences between the ILs and the cultivated parent. Among the 7,943 DE
224 genes, 2790 (35%) genes were under *cis*-regulation only, 3603 (45%) genes
225 were under *trans*-regulation only, and 1550 (20%) genes were under both *cis*-
226 and *trans*- regulation. Of these DE genes 4057 (51%) were DE in only one IL,
227 840 genes were DE in 5 or more ILs, 8 genes were DE in over 50 ILs, and a
228 single gene was DE in 70 ILs (Supplemental Dataset 2, Supplemental Figure
229 S3A). The genetic regulation of many transcripts by more than one introgression
230 and in *trans* suggests a complex genetic architecture of global transcript
231 regulation in tomato, a phenomenon noticed in many other eukaryotes such as
232 Arabidopsis, yeast, mice, and humans (Brem and Kruglyak, 2005; West et al.,
233 2007; Schadt et al., 2008).
234

235 **Global eQTL analysis at IL-bin level**

236 Identifying eQTL localized to subsets of the introgressions, based on overlaps
237 between them, enabled us to narrow down the regions that contain the regulatory
238 loci. This analysis brings us one step closer to identifying potential candidates
239 that influence gene expression patterns in tomato. The 20,795 genes with
240 sufficient read depth in the RNAseq libraries were analyzed across 74 ILs with
241 112 bins defined based on the overlap of introgression regions from *S. pennellii*
242 in the cv. M82 background (Chitwood et al., 2013) (Supplemental Figure S4). We
243 found 7,225 significant eQTL involving 5,289 unique genes across the 74 ILs
244 (Figure 2; Supplemental Dataset 3). These 7,225 significant eQTL (located in
245 bins) were assigned the following designations (Supplemental Figure S4): *cis*
246 (defined as local gene regulation within the same bin) - if the gene was located
247 on the bin it is correlated with, *trans* (distant) - if the gene was correlated with a
248 bin that is neither the bin it is on nor a bin that shares an overlapping IL with the
249 correlated bin, and *chrom0* - if the gene is not located on any of the
250 chromosomes and thus lies in the unassembled part of the genome. When a
251 gene has a designation *cis*-eQTL and a secondary correlation was found with a
252 bin that shares an overlapping introgression this secondary correlation was not
253 designated as an eQTL (Supplemental Figure S4). When a gene does not have a
254 designated *cis*-eQTL and a correlation was found with a bin that shares an
255 overlapping introgression this correlation was designated as a *trans*-eQTL
256 (Supplemental Figure S4). This resulted in a total of 1,759 *cis*-up and 1,747 *cis*-
257 down eQTL, 2,710 *trans*-up and 920 *trans*-down eQTL, and 51 *chrom0*-up and
258 38 *chrom0*-down eQTL (Spearman's rho values, Supplemental Figure S5,

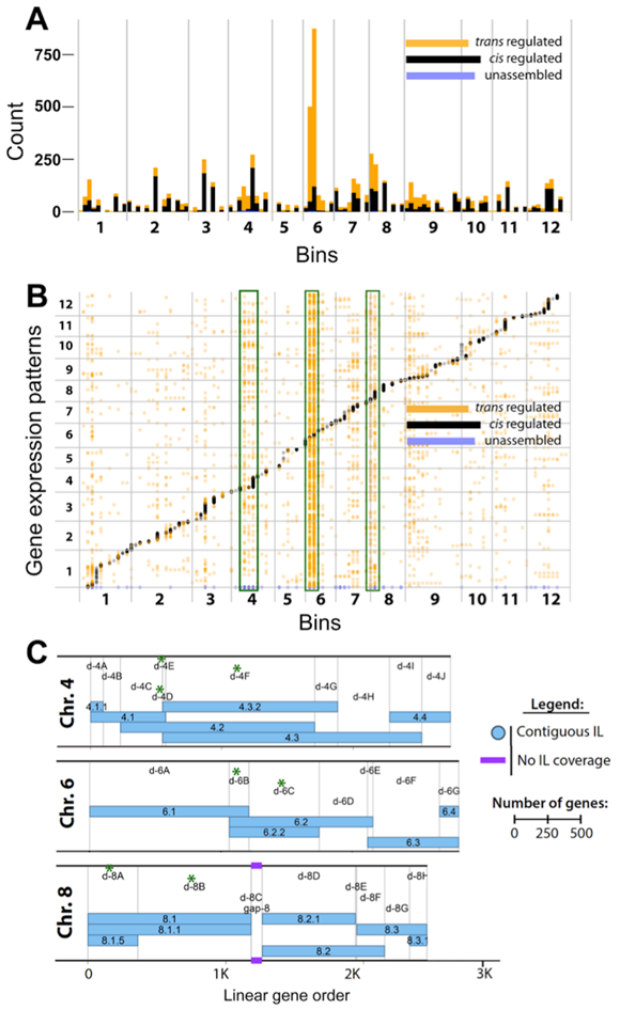

Figure 2. *Cis*- and *Trans*-eQTL plotted by bin across the 12 chromosomes of *S. lycopersicum* cv. M82. A) Stacked bar graph showing the sum of the number of eQTL mapping to each bin. B) Dotplot showing each eQTL arranged vertically by bin and horizontally by the location of the gene expression pattern it regulates. Bins with the largest numbers of *trans*-eQTL (4D, 4E, 4F, 6B, 6C, 8A, 8B) are highlighted by green boxes. C) Map of chromosomes 4, 6, and 8 showing the overlapping IL regions, which define the bins (Modified from Chitwood et al., 2013). Bins with the largest numbers of *trans*-eQTL are indicated by green asterisks.

Supplemental Table II). The majority of genes (over 4,000 out of 5,289) are under the regulation of a single eQTL (3,134 *cis*-, 1,014 *trans*-, and 19 *chromo0*-; Supplemental Figure S3B). This shows the predominance of *cis*-eQTL for genetic regulation of transcript expression patterns in the tomato ILs. Similar correlation between transcript-level variation and genome-wide sequence divergence within seven Arabidopsis accessions was reported to be due to *cis* control of a majority of the detected variation (Kliebenstein et al., 2006).

Several bins harbor a large number and/or large proportion of significant eQTL (Supplemental Dataset 4). The bins with over 100 significant *trans*-eQTL are on chromosomes 6, 8, and 4 (respectively 6C = 753, 6B = 452, 8A = 169, 8B = 128, 4D = 117). The number of genes in each bin is highly variable ranging from 1 to over 1890. Thus another metric to assess the influence of a particular bin is the number of significant *trans*-eQTL divided by total number of genes per bin. Bins with over 1.5 significant *trans*-eQTL per gene include 4D (117.0), 7D (14.7), 8C (8.0), 6B (3.0), 4E (2.5), and 3B (1.8). As expected, bins containing over 100 significant *cis*-eQTLs are scattered across the genome (Supplemental Dataset 4). Three bins, 1F, 3I and 8G, that each contain over 100 genes, have no significant *trans*- or *cis*-eQTL and are transcriptionally silent (Supplemental Dataset 4). The abundance of *trans*-eQTL on chromosomes 4, 6, and 8 strengthens the idea that *trans*-eQTL are clustered in *trans*-eQTL hotspots, as reported in other organisms, and these hotspots control the expression levels of a large number of transcripts (Brem et al., 2002; Schadt et al., 2003). The resolution in this analysis is at the level of bin, and these significant eQTL likely map to a smaller number of genes within the bins. However functional classification of genes being regulated by these eQTL and phenotypic association with the relevant ILs provides important insights into the candidate genes in the bin.

Clustering eQTL targets into modules defined by expression patterns

In order to functionally categorize the eQTL regulated genes, Barnes-Hut *t*-distributed stochastic neighbor embedding (BH-SNE, van der Maaten, 2013) was performed on the target genes to detect novel associations between gene expression patterns. The 5,289 genes with significant eQTL were mapped using BH-SNE (as explained in Materials and Methods) based on similarities in their expression patterns across the ILs. The exaggerated separation of non-neighboring clusters in this method improves 2D resolution, allowing identification of novel groupings not readily apparent in other clustering methods. This resulted in 42 distinct modules containing 3,592 genes (Figure 3). Seventeen of these modules had significant GO enrichment (p-value <0.05) with each module consisting of gene expression patterns either predominately regulated by *cis*- or *trans*-eQTL (Supplemental Table III). To determine which ILs are important for module regulation, the median expression value of module genes for each IL was calculated and used to identify ILs with significantly altered module gene expression.

Three modules were present in all mappings of the BH-SNE (van der Maaten and Hinton, 2008) determined through iterations of DBscan analysis and GO enrichment, and were designated as landmark modules (Figure 3B; Supplemental Figure S6; Supplemental Dataset 5; Supplemental Table III). The largest module had a GO enrichment for photosynthesis and related processes, and significant *trans*-eQTL scattered widely across the genome with no bin or IL identified as the primary regulating region (Figure 4B; Supplemental Figure S6A; Supplemental Dataset 5 & 6). The second landmark module was enriched for

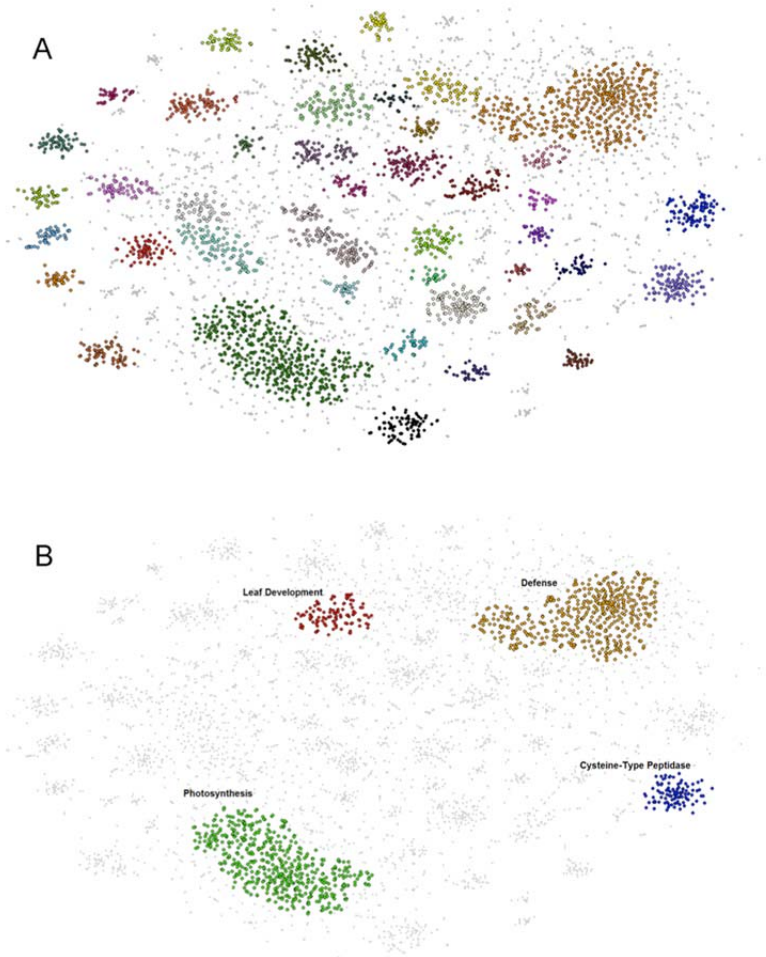

Figure 3. BH-SNE 2D mapping of eQTL. (A) Forty-two distinct modules identified by DBscan from the mapping generated by BH-SNE analysis. (B) The three modules defined as landmark modules: photosynthesis, defense and cysteine-type peptidase activity and the leaf development module's position within the mapping. Modules are false colored.

311 gene expression patterns with roles in defense, metabolism, and signaling with
312 the majority of their *trans*-eQTL mapped to IL6.2 and 6.2.2 (Figure 4A;
313 Supplemental Figure S6B; Supplemental Dataset 5 & 7). The third module, which
314 is enriched for gene expression patterns with cysteine-type peptidase activity,

315 was predominately composed of genes regulated by *cis*-eQTL on IL 4.2, 4.3, and
316 4.3.2 (Bins 4E & 4F) (Figure 4C; Supplemental Figure S6C; Supplemental
317 Dataset 5 & 8). A cluster of genes enriched for “peptidase regulation” also
318 emerged from a transcriptome study of leaf development for three tomato

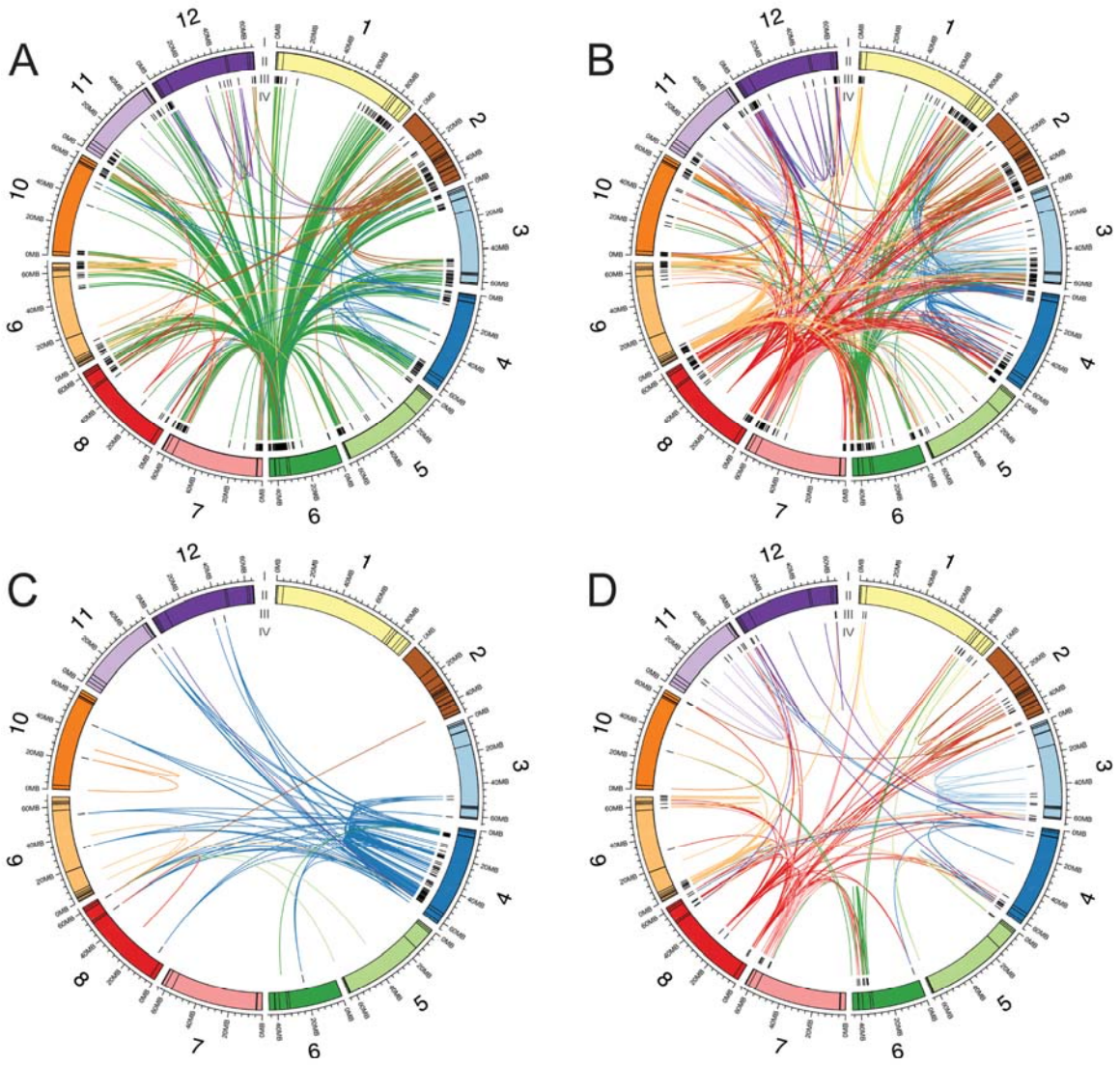

Figure 4. Connections between eQTL and the genes they regulate. Each plot includes the genes with eQTL that were clustered together into a module based on expression patterns. A) Defense module. B) Photosynthesis module. C) Cysteine peptidase module. D) Leaf development module. I) The 12 tomato chromosomes in megabases. II) Colored boxes indicate the sizes of each bin. III) Black bars indicate the locations of the genes. IV) Chords connect eQTL to the genes whose expression patterns they regulate. Chords are colored by the chromosome location of the eQTL.

species; this cluster was uniquely associated with *S. pennellii* orthologs at the P5 stage of leaf development, indicating that this species has a unique pattern of gene expression, which involves peptidase regulation (Ichihashi et al., 2014) and may be related to leaf senescence processes (Diaz-Mendoza et al., 2014).

Genetic regulation of transcriptional responses associated with plant defense

One of the landmark modules from the clustering analysis was enriched for gene expression patterns related to plant defense (Figure 3B; Supplemental Dataset 7). Therefore we explored the genetic basis of transcriptional changes associated with plant defense. IL6.2 and IL6.2.2, in particular, influence the transcriptional responses of genes associated with plant defense and signaling (Supplemental Dataset 1). The overlapping regions between IL6.2 and IL6.2.2, bins 6B and 6C, also have the largest numbers of *trans*-eQTL (Figure 4A). The genes showing increased expression in both ILs compared to cv. M82, as well as the genes regulated by the corresponding bins, show enrichment of the GO categories response to stress and stimulus, cell death, defense response, and plant-type hypersensitive response (Supplemental Dataset 9 and 10). Promoter enrichment analysis for these genes showed enrichment of a W-box promoter motif that is recognized by WRKY transcription factors and influences plant defense response (Supplemental Dataset 11 and 12) (Yu et al., 2001). Both the bins, in particular bin 6C, contain genes involved in pathogen, disease, and defense response: such as *NBS-LLR resistance genes*, *WRKY transcription factors, Multidrug resistance genes, Pentatricopeptide repeat-containing genes, Chitinase,* and *Heat Shock Protein* coding genes. These genes are known to influence plant defense responses at a global transcriptome level. The transcriptional response in the ILs is also reflected in the morphology of IL6.2.2;

346 the plants are necrotic and dwarfed (http://tgrc.ucdavis.edu/pennellii_ils.aspx,
347 (Sharlach et al., 2013). A bacterial spot disease resistance locus from *S. pennellii*,
348 *RXopJ4*, that confers hypersensitive response in IL6.2 and 6.2.2, has been
349 mapped to 190Kb region in bin 6C (Sharlach et al., 2013). In addition IL 4.1, 5.2,
350 8.1.1, and 9.1.3 also showed DE of genes involved in plant defense response,
351 though the effect of was not as strong as that of IL6.2 and 6.2.2. Taken together,
352 these findings suggest bins 6B and 6C contain master genetic regulators of plant
353 defense response genes, though identification of the causal gene/s that influence
354 so many other genes in *trans* will need further genetic dissection of these bins.
355

356 **Genetic regulation of transcriptional responses associated with leaf**
357 **development**

358 Given the striking differences in leaf features between *Solanum pennellii*
359 and cv. M82 that are manifested in many ILs (Chitwood et al., 2013), the IL
360 population provides an excellent system for determining the extent of genetic
361 regulation on leaf developmental genes. Moreover the tissues used for
362 transcriptomic analyses included developing leaves and leaf primordia. Therefore
363 we examined the effect of individual introgressions and associated bins on leaf
364 developmental genes. Previous phenotypic and QTL analyses identified many
365 ILs, such as IL4.3, IL8.1.5, IL8.1.1, and IL8.1, harboring loci regulating leaf and
366 plant developmental traits (Holtan and Hake, 2003; Chitwood et al., 2013; Muir et
367 al., 2014). IL4.3 harbors loci with the largest contribution to leaf shape, which
368 manifests as larger epidermal cell size and reduced leaf complexity (Chitwood et

369 al., 2013). This IL shows decreased expression of many genes encoding proteins
370 involved in cell division, such as Cyclin-dependent protein kinase regulator-like
371 protein (CYCA2;3), Cyclin A-like protein (CYCA3;1), CYCLIN B2;3, and F-
372 box/LRR-repeat protein 2 SKP2A (Supplemental Dataset 9). In addition, IL4.3
373 regulated genes were enriched for the promoter motifs MSA (M-specific
374 activators that are involved in M-phase specific transcription) and the E2F
375 binding site (Supplemental Dataset 11). Down-regulated genes in ILs 8.1.5,
376 8.1.1, and 8.1, also included leaf development and morphology genes, including
377 genes encoding WD-40 repeat family protein LEUNIG, Homeobox-leucine zipper
378 protein PROTODERMAL FACTOR 2, and the transcription factor
379 ULTRAPETALA (Supplemental Dataset 9; Abe et al., 2003; Cnops et al., 2004;
380 Carles et al., 2005). However target genes for none of the individual eQTL
381 showed GO enrichment associated with leaf development categories
382 (Supplemental Dataset 10). This could, in part, be due to complexity of the tissue
383 used for RNAseq analysis, as the mixture of shoot apical meristem, growing
384 leaves and hypocotyl could have diluted the significant leaf developmental genes.
385 As an alternative, we investigated the expression dynamics of a set of
386 literature-curated leaf developmental genes (Ichihashi et al., 2014) across the ILs,
387 to locate the hotspots regulating these genes (Supplemental Dataset 13). A
388 number of canonical leaf developmental genes such as *SHOOT*
389 *MERISTEMLESS* (Solyc02g081120, *STM*), *GROWTH-REGULATING FACTOR*
390 1 (*GRF1,* Solyc04g077510), *ARGONAUTE 10* (*AGO10*, Solyc12g006790), *BELL*
391 (*BEL1*, Solyc08g081400) *LEUNIG* (Solyc05g026480) and *SAWTOOTH 1* (*SAW1,*

392 Solyc04g079830) were differentially expressed in more than five ILs. At the level
393 of bins, genes involved in leaf development were seen to be regulated by eQTL
394 scattered widely across the genome (Figure 4D). This underscores the highly
395 polygenic regulation of leaf development (Chitwood et al., 2013) as multiple loci,
396 residing in many different chromosomal locations, regulate the expression of key
397 leaf-developmental genes. Fifty-eight of literature-curated leaf developmental
398 genes have expression patterns under eQTL regulation; three bins (2G, 7H, 8A)
399 each have four significant eQTL regulating leaf developmental genes, which is
400 the maximum number for any bin (Figure 4D, Supplemental Dataset 14). Bin 8A,
401 the overlapping region of IL8.1, 8.1.1, and 8.1.5, contains *LEUNIG* that showed a
402 200-fold down-regulation in the differential gene expression analysis for the three
403 ILs (Supplemental Dataset 1). Bin 8A, further, contains *trans*-eQTL that regulate
404 the expression pattern of key auxin-related genes, such as *AINTEGUMENTA*
405 *(ANT;* Solyc04g077490), and *YUCCA4* (Solyc06g065630; Supplemental Dataset
406 14). Consistent with this, IL 8.1.1, 8.1.5 and 8.1 have strong reduction in leaf
407 complexity in the direction of *S. pennellii* (Chitwood et al., 2013). Similarly IL4.3
408 contains loci with the largest contributions to leaf shape variation (Chitwood et al.,
409 2013), and also regulates the *TCP5* gene in *trans*.

410 BH-SNE clustering corroborated the strong leaf phenotypes for ILs 4.3,
411 8.1, 8.1.1, and 8.1.5. We compared a curated list of leaf developmental genes
412 combined with a set of co-expressed genes (LC+; (Ichihashi et al., 2014)) to the
413 3,592 genes found within the identified modules in the BH-SNE mapping (Figure
414 3). A total of 175 genes out of 697 from the list were found within the modules;

415 the highest concentrations were 108 genes located in the photosynthesis module
416 and 19 in the leaf development module (Supplemental Figure S7B; Supplemental
417 Dataset 15 and 16), suggesting a relationship between these two modules. The
418 eQTL regulating expression patterns of these leaf developmental genes were
419 distributed broadly across the genome (Supplemental Figure S7A, Supplemental
420 Dataset 17). This is consistent with the differential expression and eQTL
421 analyses, which found that no one bin or IL regulates leaf developmental genes.
422 Over one third of the gene expression patterns in the leaf development module
423 have significant eQTL that map to bins 4D, 8A, and 8B (5.4%, 16.2%, and 15.5%,
424 respectively), suggesting that these bins contain important regulators of leaf
425 development. The canonical leaf developmental genes within this module
426 include: *GROWTH-REGULATING FACTOR*7 (*GRF*7; Solyc03g082430); GRF10
427 (Solyc09g009200); *ERECTA-LIKE 1* (Solyc03g007050, *ERL1*); *ARGONAUTE 10*
428 (Solyc12g006790, *AGO10*); *AUXIN RESPONSE FACTOR 9* (Solyc08g008380,
429 *ARF9*); and *AINTEGUMENTA* (Solyc04g077490, *ANT*). Altogether DE, eQTL
430 and BH-SNE results indicate that while there is no obvious master regulatory bin
431 for leaf developmental genes, many are under strong genetic regulation by eQTL
432 distributed throughout the genome (Figure 4D).
433

434 **Genetic regulation of transcriptional responses associated with**
435 **photosynthesis**

436 Since photosynthesis GO terms were enriched for the largest module from
437 the clustering analysis (Figure 3B) and there was a correlation between

438 photosynthesis and leaf developmental modules (Supplemental Figure S7B), we
439 examined the genetic regulation of photosynthetic genes by specific ILs and
440 corresponding bins. Genes related to photosynthesis show increased expression
441 across 21 ILs distributed on all chromosomes except chromosome 5
442 (Supplemental Dataset 9), showing multigenic regulation of these critical traits.
443 Many of these ILs, including 8.1.5, 8.1.1, and 8.1, which share an introgressed
444 region, and IL4.3, have up-regulated genes enriched for the GO-categories
445 photosynthesis, chlorophyll biosynthesis, and response to light stimulus
446 (Supplemental Dataset 9). The eQTL target genes of corresponding bins 4D and
447 8A also have GO enrichments for photosynthesis (Supplemental Dataset 10).
448 These ILs also had significant effects on leaf shape and morphology (Chitwood
449 et al., 2013). Previously we reported a link between leaf development and
450 photosynthesis by meta-analysis of developmental and metabolic traits
451 (Chitwood et al., 2013). This indicates that ILs may also differ from each other
452 and from cultivated M82 background in photosynthetic efficiency. However no
453 studies, so far, has investigated the photosynthetic phenotype of these ILs.

454 To analyze this relationship between the leaf development and
455 photosynthesis modules the median expression value of all genes in each
456 module was compared resulting in a significant negative correlation (adj r2 =
457 0.77; Figure 5). The transition from leaf development to leaf maturation is
458 potentially reflected in our data. The genes found in the leaf development module
459 may promote developmental processes such as cell division and maintenance or
460 meristematic potential, whereas the leaf development related genes found in the

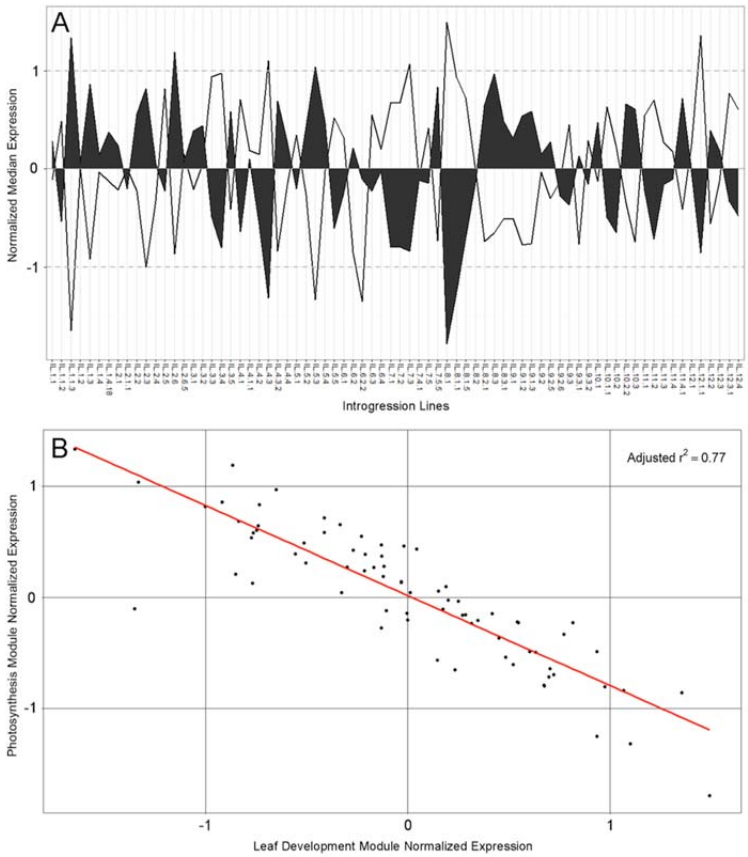

Figure 5. Median expression values for leaf development and photosynthesis related modules and expression correlation. (A) The median expression values of a module for each IL are shown. A consistent negative correlation between photosynthesis and Leaf development transcript expression is evident across nearly all 74 ILs. Dashed lines indicate one significant deviation from the module mean expression. Filled areas represent the median expression of the leaf development module, while open areas indicate the photosynthesis module median expression. (B) Leaf development median expression versus photosynthesis median expression values for each IL show a distinct negative correlation with an adjusted R-squared value of 0.77 (calculated by linear regression in R).

photosynthesis module may act to suppress this process to allow for maturation of the leaf. The strong negative correlation between the expression patterns of these two modules (Figure 5) and the overlap between their most influential eQTLs (Supplemental Figure S7A; Supplemental Table III) suggests that leaf development and photosynthetic genes not only have expression levels in opposition but also likely share common regulatory loci. Each module has eQTLs on bins 4D, 8A, and 8B which may indicate these regions drive the regulatory "switch" from development to maturation and photosynthetic activity.

Dissection of identified eQTL to spatially- and temporally- regulated development

The significant eQTL detected in this study represent the genetic regulation of gene expression in the tomato shoot apex that includes shoot apical meristem (SAM) and developing leaves. Using previous gene expression data, we spatio-temporally resolved the detected eQTL to specific tissues and temporally-regulated development. We analyzed gene expression in laser micro-dissected samples representing the shoot apical meristem (SAM) + P0 (the incipient leaf) vs. the P1 (the first emerged leaf primordium) (Figure 6A) and hand dissected samples of the SAM + P0-P4 vs. the P5 collected over time (Figure 6B-C), representing genes regulated by vegetative phase change (heteroblasty) (Chitwood et al., 2015). The former dataset represents gene expression in the meristem (SAM) and the first differentiated leaf (P1), whereas the latter dataset informs about gene expression changes during the temporal development of the shoot apex.

Using a bootstrapping approach, we identified bins statistically enriched for genetically regulating genes with previously identified gene expression patterns (Figure 6D-F). Except for one instance (cis-regulated genes with high SAM/P0 expression located in bin 2I), bins enriched for gene expression patterns represented *trans* regulation, hinting at predominately transcription factor-based regulation of gene expression patterns. Most SAM/P0 vs. P1 enriched bins were enriched for P1 gene expression (Figure 6D). We previously showed that genes with high P1 expression are enriched for photosynthetic-related GO terms,

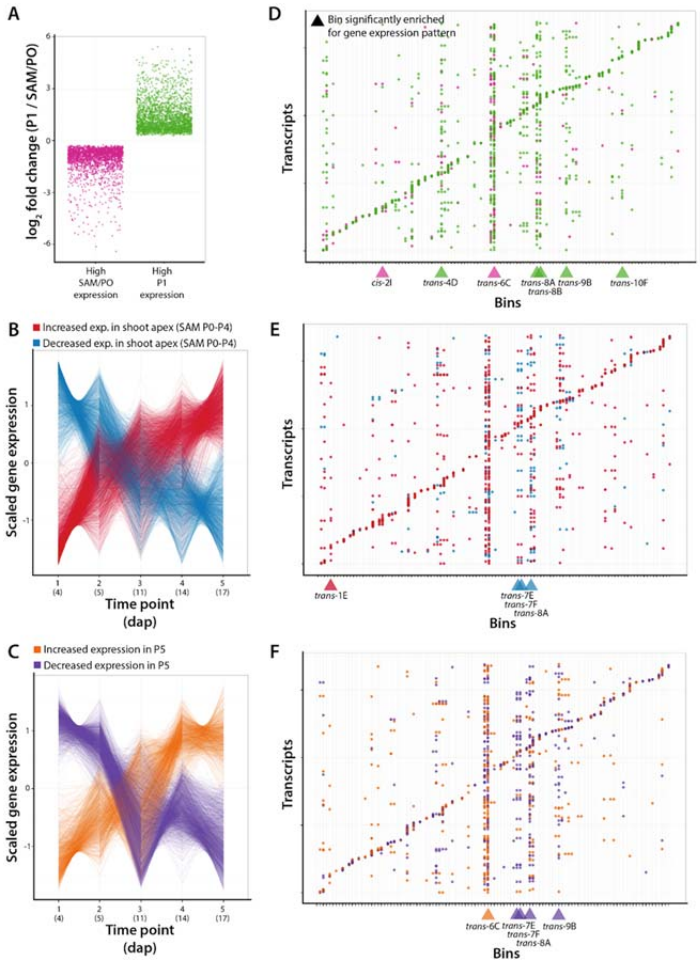

Figure 6. Enriched expression patterns for genes genetically regulated by bins.
A) Log fold change values (P1/SAM+P0) for previously identified differentially expressed genes with high expression in the SAM + P0 (magenta) vs. P1 (green). **B)** Scaled gene expression values for previously identified differentially expressed genes with increasing (red) and decreasing (blue) expression over developmental time in the SAM + P0-P4. **C)** Scaled gene expression values for previously identified differentially expressed genes with increasing (orange) and decreasing (purple) expression over developmental time in P5. **D)** Transcripts (y-axis) and bins (x-axis) showing the genetic regulation of gene expression (eQTL). Colors indicate SAM + P0 (magenta) and P1 (green) transcripts. Bins enriched for genetically regulating genes with specific expression patterns are indicated below with triangles. **E)** Same as in D), except showing genes with increasing (red) and decreasing (blue) expression over temporal time in the SAM + P0-P4. **F)** Same as in D), except showing genes with increasing (orange) and decreasing (purple) expression over temporal time in P5. Previously determined gene expression patterns are previously published (Chitwood et al., 2015).

compared to SAM/P0 genes enriched for transcription, cell division, and epigenetics-related GO terms (Chitwood et al., 2015), suggesting a genetic basis at both a functional and tissue-specific level for genes related to photosynthesis expressed preferentially in the P1 compared to the SAM/P0. Of bins enriched for SAM/P0 vs. P1 gene expression patterns, bins 4D, 8A, and 9B were significantly enriched for photosynthetic-related GO terms, indicating that these bins in

499 particular contain eQTL important for the regulation of photosynthetic processes
500 (Supplemental Dataset S18).

501 Bins enriched for regulation of genes with temporally-dependent
502 expression were mostly associated with genes with decreasing expression over
503 time, for both the SAM + P0-P4 and P5 (Figure 6E-F). Interestingly, 3 bins (7E,
504 7F, and 8A) share enrichment for genes with decreasing expression patterns
505 over time in both the SAM + P0-P4 and P5 (Figure 6E-F), suggesting true
506 temporal *trans* regulation, regardless of tissue, by these loci. Broadly, genes with
507 increasing expression over time are associated with transcription and small RNA
508 GO terms in both the SAM + P0-P4 and P5, whereas decreasing expression over
509 time is associated with translation associated GO terms in the SAM + P0-P4 and
510 photosynthetic activity in the P5. Specifically bin 6C, which was enriched for
511 genes with increasing expression over time for P5, was also significantly
512 enriched for defense processes GO terms; whereas bins 8A and 9B, that showed
513 enrichment for genes with decreasing patterns over time for P5, were enriched
514 for photosynthesis-related GO terms (Supplemental Dataset S18).

515

516 **Linking leaf and hypocotyl phenotypes to detected eQTL**

517 To better understand genetic regulation of gene expression itself, eQTL
518 provide crucial links between genetic loci and organism level phenotypes, often
519 generated in diverse tissue/organ types and environments. The tissue samples
520 used for our transcriptomic analyses contained developing leaves and hypocotyl.
521 Therefore, in order to connect detected eQTL with leaf and hypocotyl phenotypes

522 under two different environmental conditions, we correlated gene expression with
523 leaf number, leaf complexity (as measured in Chitwood et al., 2014) and
524 hypocotyl length phenotypes of the ILs grown under simulated sun and shade
525 conditions. Significant correlations with gene expression patterns were identified
526 for all three phenotypes analyzed under both treatments (Supplemental Table IV).
527 Focusing on a subset of these gene expression patterns that had associated
528 eQTL enabled us to connect the phenotypes to their regulatory loci
529 (Supplemental Table IV).

530 Genes negatively correlated with leaf number showed enrichment of leaf
531 development GO terms, whereas positively correlated genes showed enrichment
532 of photosynthesis-related GO terms (Supplemental Figure S8A-B; Supplemental
533 Dataset 2 in Chitwood et al., 2014). The expression pattern of these genes
534 associated with leaf number was predominantly regulated by eQTL on
535 chromosomes 7 and 8 (Supplemental Figure S8C-D) and reveals developmental
536 transitions reflecting a shift from leaf development to photosynthetic activity with
537 the increase in leaf number and plant maturity. For the leaf complexity trait,
538 correlations were reversed compared to leaf number, and a positive correlation
539 with genes enriched for leaf development and negative correlation with
540 photosynthesis genes was seen (Supplemental Figure S9A-B; Supplemental
541 Dataset 19). Moreover a larger number of correlations with leaf developmental
542 gene expression patterns were observed for leaf complexity in response to shade
543 (Supplemental Figure S9C-D; Supplemental Table IV). This reflects the higher
544 leaf complexity observed in shade-grown tomato plants (Xu et al., 2009;

545 Chitwood et al., 2015). eQTL on chromosomes 4, 7 and 8 were primarily involved
546 in regulation of gene expression patterns associated with leaf complexity
547 (Supplemental Figure S9C-D). These results, in combination with DE, eQTL and
548 BH-SNE, highlight bins on chromosomes 4 and 8 as important genetic regulators
549 of leaf developmental genes.

550 Five genes were positively correlated with hypocotyl length under
551 simulated shade and only one gene (Solyc10g005120) was negatively correlated
552 with hypocotyl length under both sun and shade (Figure 7A**;** Supplemental
553 Dataset 20). eQTL for the positively correlated genes are located on
554 chromosomes 3, 7, and 11, whereas the single cis-eQTL for the negatively
555 correlated gene, Solyc10g005120 (an uncharacterized *Flavanone 3-hydroxylase-*
556 *like* gene**)**, was located in bin 10A.1 (Supplemental Figure S10; Figure 7B). The
557 gene is only expressed in IL 10.1, which has the *S. pennellii* copy of the gene,
558 and not in other ILs with the M82 version of the gene, such as IL 10.1.1. Further,
559 M82 and IL 10.1.1 showed significant elongation of hypocotyls in response to
560 shade, whereas IL 10.1 had an attenuated shade avoidance response
561 (Supplemental Figure S11). This indicates the influence of genes exclusively in
562 this introgression on hypocotyl length, specifically those located in bin 10A that
563 includes Solyc10g005120. A set of BIL (Backcross Inbred Lines) lines generated
564 in a new mapping population developed from the same parents, cv. M82 and *S.*
565 *pennellii*, provides higher resolution gene mapping as bin sizes are significantly
566 smaller (Muller et al., 2016; Fulop et al., In Review). BIL-128 harbored a smaller
567 introgression on chromosome 10 compared to IL 10.1, carried the *S. pennellii*

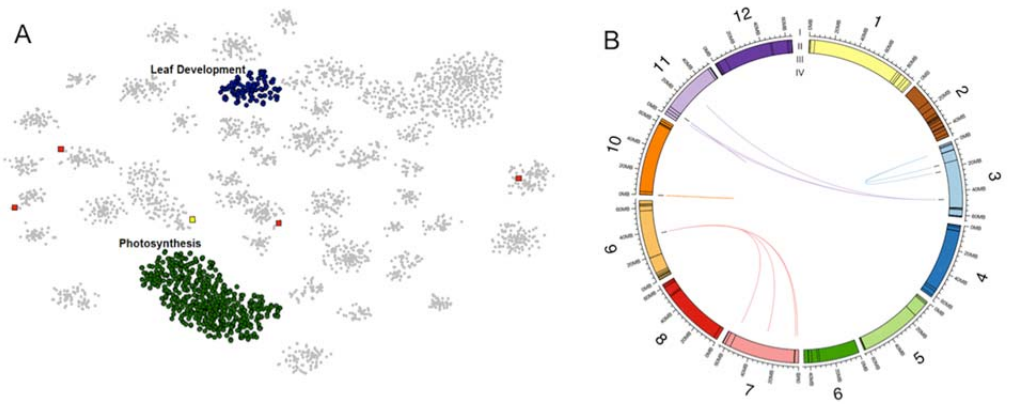

Figure 7. eQTL regulation of gene expression patterns that correlate with hypocotyl length.
A) Forty-two distinct modules identified by DBscan from the eQTL mapping generated by BH-SNE analysis. Modules enriched for genes with leaf development and photosynthesis GO terms are labeled in blue and green, respectively. Genes with expression patterns correlated with hypocotyl length under simulated shade are indicated by squares with positive correlations in red and negative correlations in yellow.
B) Genes with expression patterns correlated with hypocotyl length under simulated shade are shown connected to their respective eQTL with chords. I) The 12 tomato chromosomes in megabases. II) Colored boxes indicate the sizes of each bin. III) Black bars indicate the locations of the genes. IV) Chords connect eQTL to the genes whose expression patterns they regulate. Chords are colored by the chromosome location of the eQTL.

568 version of Solyc10g005120, and resembled IL10.1 in its hypocotyl length in
569 response to shade (Supplemental Figure S10; S11). However, it had an
570 additional introgression on chromosome 2. BIL-033 that shared an overlapping
571 introgression with BIL-128 on chromosome 2 showed a hypocotyl phenotype
572 similar to M82, ruling out the possibility of influence of chromosome 2 genes on
573 the hypocotyl phenotype (Supplemental Figure S10; S11). Though the function of
574 Solyc10g005120 has not been described for Arabidopsis or tomato so far, our
575 gene expression and phenotypic observations present it as a new potential
576 candidate for further exploring the regulation of hypocotyl length and other plant
577 phenotypes in response to shade.
578
579 **Transgressive expression of genes among ILs**

580 Interspecific crosses combining divergent genomes can sometimes result
581 in improved performance. Transcriptomic studies of wild and resynthesized
582 hybrids show extensive gene expression alterations in the hybrids compared to
583 their parents (Hegarty et al., 2008). The IL population allows us to study the
584 combination of divergent genomes across many genetically distinct lines. Many
585 of the changes we see are "transgressive", falling outside the range seen in
586 either parent. A total of 2,286 genes, more than one fourth of unique DE genes
587 between the ILs and cv. M82, showed transgressive expression patterns, i.e.
588 genes were differentially expressed for the IL but not for *S. pennellii* compared to
589 cv. M82 (Supplemental Dataset 21). These genes were distributed across all ILs
590 but the extent of transgressive gene expression varied among the ILs. ILs with
591 high number of differentially expressed genes, such as IL6.2.2, IL4.3, and IL8.1,
592 also showed higher number of transgressively expressed genes (Supplemental
593 Figure S12A). While synthetic allotetraploids generated from interspecific crosses
594 show large scale down regulation of gene expression (likely due to silencing of
595 duplicate gene copies (Wang et al., 2006)) and the affected genes fall in the
596 categories of cell defense, ageing and hormonal regulation, the transgressive
597 genes in this IL population generated by interspecific crossing show mostly
598 upregulation of gene expression with genes falling in the broad categories of
599 photosynthesis, energy metabolism, microtubule movement, and extrinsic
600 membrane components (Supplemental Dataset 22). In order to estimate the
601 relative effect of the introgression on transgressive gene expression, we
602 quantified the ratio of the number of genes with transgressive expression to the

number of genes with *S. pennellii* like expression (transgressive_to_*S. pennellii*-like) for each IL (Supplemental Figure S12B). A few ILs, such as IL1.4.18, IL4.3, IL7.3, IL8.1, IL11.1, and IL12.1.1, showed a transgressive_by_*S. pennellii* value greater than 0.5, suggesting a higher effect of the corresponding introgression on gene expression in M82 background. Most of the transgressively expressed genes for each IL were located in *trans*, beyond the introgression region (Supplemental Figure S12A). These may result from novel combinations of regulatory factors (Riddle and Birchler, 2003), recombination of alleles present at different loci in the parent species through complementary gene action (Rieseberg et al., 1999), more abundant production of small interfering (si) RNAs in progeny of interspecific crosses than in either parent with concomitant suppression of the corresponding target genes, and hypermethylation of the corresponding genomic DNA (Shivaprasad et al., 2012).

Conclusion

In this study we have investigated the regulation of gene expression in the progeny of crosses between cultivated tomato (*Solanum lycopersicum* cv. M82) and a wild relative (*Solanum pennellii*, accession LA716). A combination of differential gene expression, eQTL, and clustering analyses provide a comprehensive picture of genetic regulation of transcript expression patterns in this IL population. We show differential genetic effects of discrete genomic regions that regulate gene expression patterns. Certain regions are highly active, particularly those on chromosome 4, 6, and 8, and they influence the expression

626 patterns of genes in their own introgression regions and beyond. Clustering of
627 genes by expression patterns and GO/promoter motif enrichment analyses
628 provided further insights into the genetic regulation of expression patterns of
629 genes related to specific pathways. Our data show that some biological pathways,
630 such as plant defense, are under the regulation of a limited number of loci with
631 strong effects, whereas loci regulating other pathways, such as photosynthesis
632 and leaf development, are scattered throughout the genome most likely with
633 weaker individual effects. Using published gene expression atlases for tomato we
634 were able to partition the eQTLs into tissue specific and age dependent patterns
635 of expression. We correlated gene expression with leaf and hypocotyl
636 phenotypes and identified the regulatory regions driving these gene expression
637 patterns. In the case of hypocotyl length we identified a strong candidate gene
638 that may regulate hypocotyl length under shade avoidance. This is the first
639 comprehensive insight into the global regulation of transcript abundance in
640 tomato and sets the stage for identification of gene/s underlying these regulatory
641 loci. Coupled with comprehensive phenotyping on these ILs this data set
642 provides insights into how the expression pattern of key genes or gene modules
643 can be genetically manipulated to achieve a desirable plant phenotype. We
644 report on differential gene expression between the ILs and the recurrent parent,
645 M82, eQTLs that regulate thee gene expression patterns and transgressive
646 changes in gene expression. Together these facets of change in gene
647 expression may explain hybrid performance, and could provide genotypes that
648 have an enhanced ability to survive in habitats not accessible to the parents.

While they may provide avenues for enhancing breeding efforts, they also reveal unexpected consequences of wide crosses. A study of transcriptional variation is only one component of many others, such as protein and metabolite levels, to influence downstream phenotypes. Given a number of important plant traits have complex inheritance, transcript abundance can function as an intermediate between genomic DNA sequence variation and complex traits. Our ability to predict and understand the downstream effects of genes introgressed from wild relatives on gene expression patterns and ultimately phenotypes will be a critical component of crop plant enhancement.

Materials and Methods

Plant Materials, Growth Conditions, and Experimental Design

Plant materials, growth conditions, and experimental design were described in (Chitwood et al., 2013), but are outlined here briefly. Seeds of *Solanum pennellii* ILs (Eshed and Zamir, 1995; Liu and Zamir, 1999) and *Solanum lycopersicum* cv. M82 were obtained either from Dani Zamir (Hebrew University, Rehovot, Israel) or from the Tomato Genetics Resource Center (University of California, Davis). Seeds were stratified in 50% bleach for 2 min., grown in darkness for 3 d for uniform germination before moving to a growth chambers for 5 days. Six seedlings of each genotype were planted per pot for each replicate. The 76 ILs (and two replicates each of cv. M82 and *S. pennellii*) were divided into four cohorts of 20 randomly assigned genotypes. These cohorts were placed across

672 four temporal replicates in a Latin square design as described in (Chitwood et al.,
673 2013). The seedlings were harvested 5 d after transplanting (13 d of growth in
674 total). Cotyledons and mature leaves >1 cm in total length were excluded, and
675 remaining tissues (including the shoot apical meristem) above the midpoint of the
676 hypocotyl were pooled, for all individuals in a pot, into 2-mL microcentrifuge
677 tubes and immediately frozen in liquid nitrogen. Two ILs, IL7.4 and IL12.4.1 were
678 not included in the final analysis due to seed contaminations.
679

680 **Growth conditions and quantification of hypocotyl length**

681 Seeds 76 ILs along with the parents were sterilized using 70% ethanol,
682 followed by 50% bleach, and finally rinsed with sterile water. This experiment
683 was replicated three times each in 2011 and 2012. Ten to twelve seeds of each
684 IL were sown into Phytatray II (Sigma-Aldrich) containers with 0.5x Murashige
685 and Skoog minimal salt agar. Trays were randomized and seeds germinated in
686 total darkness at room temperature for 48h. Trays of each IL were randomly
687 assigned to either a sun or shade treatment consisting of 110μMol PAR with a
688 red to far-red ratio of either 1.5 (simulated sun) or 0.5 (simulated shade) at 22°C
689 with 16 hour light / 8 hour dark cycles for 10d. Three genotypes were excluded
690 from the analyses due to poor germination (IL3.3) or their necrotic dwarf
691 phenotypes (IL6.2, 6.2.2). After 10d, seedlings were removed from the agar and
692 placed onto transparency sheets containing a moistened kimwipe to prevent
693 dehydration and scanned using an Epson V700 at 8-bit grayscale at 600 dpi.
694 Image analysis was carried out using the software ImageJ (Abramoff et al., 2004).

For hypocotyl length analysis of backcross inbred lines between *S. pennellii* and *S. lycopersicum* cv. M82, seeds were sterilized in 50% bleach and then rinsed with sterile water. They were then placed in Phytatrays in total dark at room temperature for 72 hours, and then moved to 16 hour light / 8 hour dark for 4d. Seedlings were transferred to soil using a randomized design and assigned to either a sun or shade treatment (as described above) for seven days. Images were taken with a HTC One M8 Dual 4MP camera and hypocotyl lengths measured in ImageJ (Abramoff et al., 2004) using the Simple Neurite Tracer (Longair et al., 2011) plugin.

Correlation of phenotype with gene expression pattern

Gene expression patterns were correlated with three phenotypes collected from the ILs along with the parents. Normalized estimated read counts with 3-4 independent replicates per IL were log2 transformed prior to the analyses. Leaf number and leaf complexity were collected from the ILs as outlined in Chitwood et al. (2014) under both sun and shade treatments. Hypocotyl lengths were measured as detailed above. To test whether a gene's expression pattern was correlated with a particular phenotype boostrapping analyses were performed. Expression and phenotype data were randomly permuted (with replacement) using the sample() function against IL and then merged. For each analysis, 1000 replications were performed and the p-values were calculated from the Spearman's rho value distributions. P-values were adjusted for multiple comparisons using the BH correction (Benjamini & Hochberg, 1995). Significant

718 correlations were identified as those with an adjusted p-value < 0.05 and the
719 mean rho value (the correlation coefficient) was used to designate the correlation
720 as either positive (positive slope) or negative (negative slope). All analyses were
721 implemented using the statistical software R and custom scripts (R Core Team,
722 2015).
723

724 **RNA-Seq Library Preparation and Preprocessing RNA-Seq Sequence Data**

725 RNAseq libraries were prepared and the reads were preprocessed as described
726 in (Chitwood et al., 2013), and are outlined here. mRNA isolation and RNA-Seq
727 library preparation were performed from 80 samples at a time using a high-
728 throughput RNA-Seq protocol (Kumar et al., 2012). The prepared libraries were
729 sequenced in pools of 12 for replicates 1 and 2 (one lane each) and in pools of
730 80 for replicates 3 and 4 (seven lanes) at the UC Davis Genome Centre
731 Expression Analysis Core using the HiSeq 2000 platform (Illumina).
732 Preprocessing of reads involved removal of low quality reads (phred score < 20),
733 trimming of low-quality bases from the 39 ends of the reads, and removal of
734 adapter contamination using custom Perl scripts. The quality-filtered reads were
735 sorted into individual libraries based on barcodes and then barcodes were
736 trimmed using custom Perl script.
737

738 **Read Mapping and Gene Expression Analysis**

739 Mapping and normalization were done on the iPLANT Atmosphere cloud server
740 (Goff et al., 2011). *S. lycopersicum* reads were mapped to 34,727 tomato cDNA

741 sequences predicted from the gene models from the ITAG2.4 genome build
742 (downloadable from
743 ftp://ftp.solgenomics.net/tomato_genome/annotation/ITAG2.4_release/). A
744 pseudo reference list was constructed for *S. pennellii* using the homologous
745 regions between *S. pennellii* scaffolds v.1.9 and *S. lycopersicum* cDNA
746 references above. Using the defined boundaries of ILs, custom R scripts were
747 used to prepare IL-specific references that had the *S. pennellii* sequences in the
748 introgressed region and *S. lycopersicum* sequences outside the introgressed
749 region. The reads were mapped using BWA (Li and Durbin, 2009; Roberts and
750 Pachter, 2013) using default parameters except for the following that were
751 changed: bwa aln: -k 1 -l 25 -e 15 -i 10 and bwa samse: -n 0. The bam alignment
752 files were used as inputs for express software to account for reads mapped to
753 multiple locations (Roberts and Pachter, 2013). The estimated read counts
754 obtained for each gene for each sample from express were treated as raw counts
755 for differential gene expression analysis. The counts were then filtered in R using
756 the Bioconductor package EdgeR version 2.6.10 (Robinson and Oshlack, 2010)
757 such that only genes that have more than two reads per million in at least three
758 of the samples were kept. Normalization of read counts was performed using the
759 trimmed mean of M-values method (Robinson and Oshlack, 2010), and
760 normalized read counts were used to identify genes that are differentially
761 expressed in each IL compared to cv. M82 parent as well as in between two
762 parents, *S. pennellii* and M82. The DE genes for each IL were compared to those
763 between the two parents to identify genes that were differentially expressed for

764 the IL but not for *S. pennellii* compared to cv. M82. Those genes were
765 considered to show transgressive expression pattern for the specific IL, whereas
766 other DE genes were considered to show *S. pennellii* like expression pattern.
767

768 **Methods for eQTL Analyses**

769 eQTL mapping analyses were performed to determine whether the expression
770 pattern of a gene is correlated with the presence of a specific introgression from
771 *S. pennellii* into *S. lycopersicum* cv. M82. This was examined at the level of "bin",
772 with a bin defined as a unique overlapping region between introgressions.
773 Examining eQTL at the bin level enables them to be mapped to considerably
774 smaller intervals than the ILs themselves (Liu and Zamir, 1999). eQTL mapping
775 analyses were performed on the normalized estimated read counts with 3-4
776 independent replicates per IL, which were log2 transformed prior to the analyses.
777 To test whether a gene's expression pattern is correlated with the presence of a
778 particular bin a Spearman's rank correlation test was used with ties resolved
779 using the midrank method. P-values were adjusted for multiple comparisons
780 using the BH correction (Benjamini and Hochberg, 1995). Significant eQTL were
781 identified as those with an adjusted p-value < 0.05 and Spearman's rho (the
782 correlation coefficient) was used to designate the eQTL as up (positive slope) or
783 down (negative slope). All analyses were implemented using the statistical
784 software R and custom scripts (R Core Team, 2015).
785

786 **Methods for eQTL clustering analysis**

787 **Data Preparation:** In preparation for analysis using the Barnes-Hut-SNE
788 algorithm the data set was log2 transformed. Each gene's expression profile was
789 then normalized across all 74 introgression lines so that the profile had a mean of
790 zero and a standard deviation of one. Normalization of the data allowed for
791 comparison of the relative relationship between each gene expression profile
792 (Bushati et al., 2011).

793 **Barnes-Hut-SNE:** *t*-SNE or *t*-distributed stochastic neighbor embedding (van
794 der Maaten and Hinton, 2008) is a non-linear dimensionality reduction method,
795 which faithfully maps objects in high dimensional space (H-space) into low
796 dimensional space (V-space). Crowding is avoided through the long-tailed *t*-
797 distribution, which forces non-neighbor clusters farther away from each other in
798 V-space than they actually are in H-space (van der Maaten and Hinton, 2008).
799 The exaggerated separation of non-neighboring clusters improves 2D resolution,
800 allowing identification of novel groupings not readily apparent in other clustering
801 methods. However, this method is resource intensive and with higher
802 dimensionality the number of genes that can be analyzed is limited. Because of
803 this, Barnes-Hut-SNE a newer implementation of *t*-SNE was used, which greatly
804 increases the speed and number of genes that can be analyzed (van der Maaten,
805 2013). It accomplishes this through the use of a Vantage Point tree and a variant
806 of the Barnes-Hut algorithm (van der Maaten, 2013). For clustering, 2D maps
807 were generated using a perplexity of 30 and without the initial PCA step from the
808 Barnes-Hut-SNE R implementation (Rtsne package; (Krijthe, 2014)). Theta was

809 set to 0.3 based on (van der Maaten, 2013) in order to maintain an accurate
810 dimensionality reduction without sacrificing processing speed.
811 **Clustering for Module Selection:** The DBscan algorithm (Density Based spatial
812 clustering of applications with noise) was used to select modules from the
813 Barnes-Hut-SNE results (fpc package; (Hennig, 2014)). This had the advantage
814 of both selecting modules and removing any genes that fell between modules.
815 The scanning range (*epsilon*) and minimum seed points (*minpts*) were selected
816 manually, and used to determine if any one point is a member of a cluster based
817 on physical positioning within the mapping relative to neighboring points.. A
818 *minpts* of 25 was used to capture smaller modules on the periphery and an
819 *epsilon* of 2.25 was used to avoid the overlapping of internal and closely spaced
820 modules.
821 **Plots:** Boxplots were generated from normalized expression values for each
822 module. The ribbon plot was generated from correlated expression values from
823 leaf development and photosynthesis related modules. These plots were
824 generated using ggplot form the ggplot2 R Package (Wickham, 2009). The
825 median expression of the genes mapped to a module was calculated for each IL
826 and replicated for all modules. Significant ILs were identified as those with a
827 median expression greater than 1 standard deviation from the mean of all genes
828 across all ILs in the module.
829
830 **GO Enrichment analysis**

Differentially expressed genes for individual ILs and Genes with significant eQTL were analyzed for enrichment of Gene Ontology (GO) terms at a 0.05 false discovery rate cutoff (goseq Bioconductor package; Young et al., 2010).

Promoter enrichment analysis

Promoter enrichment analysis was performed by analyzing the 1000 bp upstream of the ATG translational start site for genes with significant eQTL using 100 motifs represented in the AGRIS AtTFDB (http://arabidopsis.med.ohio-state.edu/AtTFDB). The Biostrings package was used to analyze the abundance of 100 motifs in groups of genes with significant eQTL compared to motif abundance in promoters of all analyzed genes using a Fisher's exact test ($p < 0.05$) with either zero or one mismatch (Ichihashi et al., 2014).

Dissection of eQTL to different stages and time of development at shoot apex

Differentially expressed genes with enriched expression in laser micro-dissected SAM/P0 vs. P1 samples or hand-dissected samples of the SAM + P0-P4 or P5 sampled over developmental time were obtained from Chitwood et al., 2015. Genes for which a differential expression call could be made (i.e., had enough reads and passed quality filters) were merged with detected eQTL using the merge() function in R (R Core Team, 2015). For bootstrapping, *cis*- and *trans*-regulated transcripts were analyzed separately. Merged gene expression patterns were randomly permuted (without replacement) using the sample()

function against bin identity. For each test, 10,000 permutations were sampled to count the times that a particular expression pattern was assigned to a bin more than the actual count. Resulting frequencies, representing a probability value, were multiple test adjusted using the Benjamini-Hochberg (Benjamini and Hochberg, 1995) method using p.adjust(). Those bins with multiple test adjusted probability values <0.05 were analyzed further using visualizations created with ggplot2 (Wickham, 2009).

Sequence submission

The quality filtered, barcode-sorted and trimmed short read dataset, which was used to get the normalized read counts and for differential gene expression analysis, was deposited to the NCBI Short Read Archive under accessions SRR1013035 - SRR1013343 (Bioproject accession SRP031491).

Supplemental files

Supplemental figures:

Supplemental Figure S1. Number of genes in the introgression region for an IL and the number of differentially expressed genes compared to cv. M82. Strong correlation was observed for differentially expressed genes in *cis* (A), whereas a weak correlation was observed for genes in *trans* (B).

Supplemental Figure S2. Histograms for differentially expressed genes for the ILs. Up-regulated and down-regulated genes for the ILs in *cis* (A), and in *trans* (B).

Supplemental Figure S3. Frequency and distribution of differentially expressed genes for the IL population at the introgression and the bin level. (A) Frequency of genes differentially expressed in one or more ILs. (B) Frequency of genes being regulated by one or more BINs/eQTL. (C) Distribution of genes under one or more eQTL regulation for the IL population on different chromosomes

Supplemental Figure S4. eQTL and the gene expression pattern they regulate. Each blue bar is a unique introgression. When the gene expression pattern of gene 1 is correlated with bin-A, then bin-A contains a *cis*-eQTL. When the gene expression pattern of gene 1 is correlated with bin-E then bin-E contains a *trans*-eQTL. When gene 2 has a *cis*-eQTL designated for bin-D and the gene expression pattern of gene 2 is also correlated with bin-B, then this secondary correlation is not designated as an eQTL, since these bins share overlapping introgression regions. When the gene expression pattern of gene 2 is correlated with bin-B and gene 2 does not have a *cis*-eQTL designated for bin-D, then bin-B is designated as a *trans*-eQTL. All eQTLs for genes that lie in the unassembled portion of the genome (not on any chromosome) cannot be designated as either *cis*- or *trans*- and are designated *chromo0*-eQTL.

Supplemental Figure S5. *Cis*- and *Trans*-eQTL. Histograms plotting the numbers of significant eQTL mapped to each bin across the 12 chromosomes of *S. lycopersicum* (M82). A. *cis*-eQTLs. B. *trans*-eQTLs.

Supplemental Figure S6. Boxplots of the normalized expression patterns for the three landmark modules. The relative expression of all genes found in each module for the 74 IL's. The y-axis is the relative expression of all eQTL for each IL. (A) Photosynthesis module. (B) Defense, metabolism, and signaling module. (C) Cysteine-type peptidase activity module. Asterisks represent ILs with a median expression significantly different from the module mean.

Supplemental Figure S7. Normalized expression of the leaf development module and leaf developmental genes within the mapping. (A) Boxplot of normalized expression pattern for the leaf development module. The 108 genes contained in the leaf development module and their relative median expression for each IL. Asterisks represent ILs with a median expression significantly different from the module mean. (B) LC+ list of leaf developmental genes overlaid on the Leaf Development and Photosynthesis modules. False colored orange, dark blue, and light blue respectively.

Supplemental Figure S8. eQTL regulation of gene expression patterns that correlate with leaf number.

921 A, B) Forty-two distinct modules identified by DBscan from the eQTL mapping
922 generated by BH-SNE analysis. Modules enriched for genes with leaf
923 development and photosynthesis GO terms are labeled in blue and green,
924 respectively. Genes with expression patterns correlated with leaf number under
925 simulated sun (A) and shade (B) are indicated by squares with positive
926 correlations in red and negative correlations in yellow.
927 C, D) Genes with expression patterns correlated with leaf number under
928 simulated sun (C) and shade (D) are shown connected to their respective eQTL
929 with chords. I) The 12 tomato chromosomes in megabases. II) Colored boxes
930 indicate the sizes of each bin. III) Black bars indicate the locations of the genes.
931 IV) Chords connect eQTL to the genes whose expression patterns they regulate.
932 Chords are colored by the chromosome location of the eQTL.
933
934 **Supplemental Figure S9. eQTL regulation of gene expression patterns that**
935 **correlate with leaf complexity.**
936 A, B) Forty-two distinct modules identified by DBscan from the eQTL mapping
937 generated by BH-SNE analysis. Modules enriched for genes with leaf
938 development and photosynthesis GO terms are labeled in blue and green,
939 respectively. Genes with expression patterns correlated with leaf complexity
940 under simulated sun (A) and shade (B) are indicated by squares with positive
941 correlations in red and negative correlations in yellow.
942 C, D) Genes with expression patterns correlated with leaf complexity under
943 simulated sun (C) and shade (D) are shown connected to their respective eQTL

944 with chords. I) The 12 tomato chromosomes in megabases. II) Colored boxes
945 indicate the sizes of each bin. III) Black bars indicate the locations of the genes.
946 IV) Chords connect eQTL to the genes whose expression patterns they regulate.
947 Chords are colored by the chromosome location of the eQTL.
948
949 **Supplemental Figure S10. Distributions of introgressions from *S. pennellii***
950 **into *S. lycopersicum* cv. M82.** Map of chromosomes 2, 10, and 11 showing the
951 locations of the introgressions for BIL 033 and 128, as well as the overlapping IL
952 regions, which define the bind (Modified from Chitwood et al., 2013).
953
954 **Supplemental Figure S11. Tomato hypocotyl length under sun and shade**
955 **treatments.** M82 shows a typical shade response with a significantly longer
956 hypocotyl in the shade (Δ of 7 mm). IL 10.1 and BIL 128, which share an
957 overlapping introgression (**Supplemental Fig. BIL**), do not significantly respond
958 to the shade treatments. The presence of a response in BIL 033 in combination
959 with the shared introgression with BIL 128 on chromosome 2, indicates that the
960 gene region responsible for the lack of shade response in BIL 128 is located in
961 the introgression on chromosome 10. Bars represent means +/- SE with a
962 minimal of N = 22 for each (ANOVA, $F_{7,182}$ = 44.6, p < 0.001). Letters indicate
963 differences at the p < 0.05 significance level for Tukey pairwise tests.
964
965 **Supplemental Figure S12. Quantification of genes with transgressive**
966 **expression pattern in the IL population** (A) Number of genes showing

transgressive expression for each IL along with their location in *cis* or *trans*. (B) Ratio of number of genes with transgressive expression to number of genes with *S. pennellii* like expression (transgressive to *S. pennellii*-like) for each IL**.**

<u>Supplemental tables:</u>

Supplemental Table I. Number of differentially expressed (DE) genes in *cis*, *trans*, and the total number of DE genes for the ILs along with number of genes in the introgression region.

Supplemental Table II. Correlation coefficients (Spearman's rho) for significant eQTLs. Divided into *trans*-, *cis-,* and *chromo0-,* then designated as up (positive slope) or down (negative slope) based on the correlation coefficients.

Supplemental Table III. GO enrichment and *cis* or *trans* regulation of the 42 identified modules. All 42 distinct modules are listed with the total number of genes present in each module. The GO enrichment (if one is present) is given for each module, along with whether that module is predominantly *cis* or *trans* regulated. Only nine of the forty two module show *trans* correlation, which includes the leaf development module.

Supplemental Table IV. Significant correlations between gene expression patterns and phenotypes. Bootstrapping analyses correlated gene expression

patterns across the 74 ILs with three phenotypes in under both sun and shade treatments. Genes with significant correlations that also have eQTL are listed.

Supplemental datasets:

Supplemental Dataset 1. List of Differentially Expressed Genes. List of significant (FDR < 0.05) differentially expressed genes for each Introgression line (IL) compared to cultivated parent *Solanum lycopersicum* cv. M82. For each IL, gene ID, log Fold Change (logFC), log Counts Per Million (logCPM), P-value, False Discovery Rate (FDR) as well as annotation of the differentially expressed genes are presented.

Supplemental Dataset 2. Frequency of differentially expressed genes among the ILs (Genes that show differential expression in at least one IL are listed).

Supplemental Dataset 3. All eQTL. All significant eQTL with AGI and ITAG annotations added.

Supplemental Dataset 4. Number of eQTL per bin.

Supplemental Dataset 5. Number of eQTL and the bin on which they reside for each of the landmark modules. The Photosynthesis, Defense and Cysteine-Type Peptidase Activity modules are listed with the bins on which their eQTL reside. The number eQTL per bin and the percentage of total eQTL within each module is listed.

Supplemental Dataset 6. Module Gene List. Listing of all genes within the Photosynthesis module with Gene ID and Description.

Supplemental Dataset 7. Module Gene List. Listing of all genes within the Defense module with Gene ID and Description.

Supplemental Dataset 8. Module Gene List. Listing of all genes within the Cysteine-type Peptidase module with Gene ID and Description.

Supplemental Dataset 9. GO Enrichment for DE Genes. Enriched GO and GOslim categories for the up- and down-regulated genes in each IL compared to cultivated parent *Solanum lycopersicum* cv. M82.

Supplemental Dataset 10. GO Enrichment for eQTL. GO and GO SLIM enrichment results for all the eQTL mapped to a bin, as well as the *cis*- and *trans*-eQTL separately.

Supplemental Dataset 11. Promoter Motif Enrichment for DE Genes. Enriched promoter motifs with no mismatch for the up- and down-regulated genes in each IL compared to cultivated parent *Solanum lycopersicum* cv. M82.

1034 **Supplemental Dataset 12. Enriched promoter motifs for *trans*-eQTLs**
1035 **mapped to each bin.**
1036

1037 **Supplemental Dataset 13. Differentially expressed leaf Developmental**
1038 **Genes.** Frequency of differentially expressed literature-curated leaf-
1039 developmental genes among the ILs (Genes that show differential expression in
1040 at least one IL are listed).

1041

1042 **Supplemental Dataset 14. Curated list of leaf developmental genes with**
1043 **eQTLs.**
1044

1045 **Supplemental Dataset 15. Literature-curated plus list of leaf development**
1046 **genes present in the leaf development modules.** Nineteen genes from the
1047 literature-curated plus list (Ichihashi et al., 2014) were present within the leaf
1048 development module, representing approximately 3% of the curated genes and
1049 11% of the curated genes found in the eQTL data set. The Gene ID, *Arabidopsis*
1050 orthologue, and a description for each gene is provided.
1051

1052 **Supplemental Dataset 16. Literature-curated plus list of leaf development**
1053 **genes that are present in all modules.** A total of 175 genes from the curated
1054 list plus of leaf developmental genes (Ichihashi et al., 2014) were present in the
1055 5289 genes with significant eQTL. Matching gene number is the number of
1056 genes in the module, which were found in the curated list. The percent of curated

genes defines the percentage of matched genes in a module out of the total curated list plus. The percent total in eQTL represents the percentage of matched genes in a module out of the 175 present only in the eQTL. The Photosynthesis and leaf development modules contain the highest proportion of leaf development curated genes.

Supplemental Dataset 17. Module Gene List. Listing of all genes within the Leaf Development module with Gene ID and Description.

Supplemental Dataset 18: GO enrichment results for bins statically enriched for genes expressed spatio-temporally across tissues.

Supplemental Dataset 19: Total leaf complexity data for all the ILs under simulated sun and shade.

Supplemental Dataset 20: Hypocotyl length data for all the ILs under simulated sun and shade for two years.

Supplemental Dataset 21. Genes with Transgressive Expression. List of the genes showing transgressive expression in the IL population along with details of their expression and annotation.

1079 **Supplemental Dataset 22. GO Enrichment for Transgressive Expression.**
1080 Enriched GO-categories for the genes showing transgressive expression in the IL
1081 population.
1082

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1091

1092 Authors' contributions

1093 DHC, JNM and NRS conceived and designed the experiments. AR, DHC, RK,
1094 LC, YI and KZ performed the experiments. AR, JMB and SDR analyzed the data.
1095 AR, JMB, SDR, DHC and JNM contributed reagents/materials/analysis tools. AR,
1096 JMB, SDR and NRS wrote the paper. All authors read and approved the final
1097 manuscript.
1098

Figure legends:

Figure 1. Transcriptome profile of the tomato introgression lines. Differentially expressed genes for the ILs compared to cultivated parent M82. Y-axis shows all the tomato genes starting from the first gene on chromosome 1 to the last gene on chromosome 12, and X-axis depicts the individual ILs. Genes differentially expressed within the introgression regions (in *cis*) are shown as blue points and differentially expressed genes in *trans* (outside) the introgression region are shown as orange points.

Figure 2. *Cis*- and *Trans*-eQTL plotted by bin across the 12 chromosomes of *S. lycopersicum* cv. M82. A) Stacked bar graph showing the sum of the number of eQTL mapping to each bin. B) Dotplot showing each eQTL arranged vertically by bin and horizontally by the location of the gene expression pattern it regulates. Bins with the largest numbers of *trans*-eQTL (4D, 4E, 4F, 6B, 6C, 8A, 8B) are highlighted by green boxes. C) Map of chromosomes 4, 6, and 8 showing the overlapping IL regions, which define the bins (Modified from Chitwood et al., 2013). Bins with the largest numbers of *trans*-eQTL are indicated by green asterisks.

Figure 3. BH-SNE 2D mapping of eQTL. (A) Forty-two distinct modules identified by DBscan from the mapping generated by BH-SNE analysis. (B) The three modules defined as landmark modules: photosynthesis, defense and

cysteine-type peptidase activity and the leaf development module's position within the mapping. Modules are false colored.

Figure 4. Connections between eQTL and the genes they regulate. Each plot includes the genes with eQTL that were clustered together into a module based on expression patterns. A) Defense module. B) Photosynthesis module. C) Cysteine peptidase module. D) Leaf development module. I) The 12 tomato chromosomes in megabases. II) Colored boxes indicate the sizes of each bin. III) Black bars indicate the locations of the genes. IV) Chords connect eQTL to the genes whose expression patterns they regulate. Chords are colored by the chromosome location of the eQTL.

Figure 5. Median expression values for leaf development and photosynthesis related modules and expression correlation. (A) The median expression values of a module for each IL are shown. A consistent negative correlation between photosynthesis and Leaf development transcript expression is evident across nearly all 74 ILs. Dashed lines indicate one significant deviation from the module mean expression. Filled areas represent the median expression of the leaf development module, while open areas indicate the photosynthesis module median expression. (B) Leaf development median expression versus photosynthesis median expression values for each IL show a distinct negative correlation with an adjusted R-squared value of 0.77 (calculated by linear regression in R).

1145

1146 **Figure 6. Enriched expression patterns for genes genetically regulated by**
1147 **bins. A)** Log fold change values (P1/SAM+P0) for previously identified
1148 differentially expressed genes with high expression in the SAM + P0 (magenta)
1149 vs. P1 (green). **B)** Scaled gene expression values for previously identified
1150 differentially expressed genes with increasing (red) and decreasing (blue)
1151 expression over developmental time in the SAM + P0-P4. **C)** Scaled gene
1152 expression values for previously identified differentially expressed genes with
1153 increasing (orange) and decreasing (purple) expression over developmental time
1154 in P5. **D)** Transcripts (y-axis) and bins (x-axis) showing the genetic regulation of
1155 gene expression (eQTL). Colors indicate SAM + P0 (magenta) and P1 (green)
1156 transcripts. Bins enriched for genetically regulating genes with specific
1157 expression patterns are indicated below with triangles. **E)** Same as in D), except
1158 showing genes with increasing (red) and decreasing (blue) expression over
1159 temporal time in the SAM + P0-P4. **F)** Same as in D), except showing genes with
1160 increasing (orange) and decreasing (purple) expression over temporal time in P5.
1161 Previously determined gene expression patterns are previously published
1162 (Chitwood et al., 2015).

1163

1164 **Figure 7. eQTL regulation of gene expression patterns that correlate with**
1165 **hypocotyl length.**
1166 A) Forty-two distinct modules identified by DBscan from the eQTL mapping
1167 generated by BH-SNE analysis. Modules enriched for genes with leaf

development and photosynthesis GO terms are labeled in blue and green, respectively. Genes with expression patterns correlated with hypocotyl length under simulated shade are indicated by squares with positive correlations in red and negative correlations in yellow.

B) Genes with expression patterns correlated with hypocotyl length under simulated shade are shown connected to their respective eQTL with chords. I) The 12 tomato chromosomes in megabases. II) Colored boxes indicate the sizes of each bin. III) Black bars indicate the locations of the genes. IV) Chords connect eQTL to the genes whose expression patterns they regulate. Chords are colored by the chromosome location of the eQTL.

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