Hello darkness, my old friend: 3-Ketoacyl-Coenzyme A Synthase4 is a branch point in the regulation of triacylglycerol synthesis in Arabidopsis by re-channeling fatty acids under carbon starvation

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Running title: KCS4 impacts lipid remodeling under C-starvation

Keywords: Arabidopsis, GWAS, natural variation, triacylglycerols, fatty acids, KCS4, carbon starvation

One sentence summary:

Natural variation at *KCS4* underlies a differential accumulation of polyunsaturated triacylglycerols, by acting as a regulatory branch point in the fate of fatty acids under carbon starvation.

Abstract

Due to their sessile lifestyle, plants have evolved unique mechanisms to deal with environmental challenges. Under stress, plant lipids are important as alternative sources of carbon and energy when sugars or starch are limited. Here, we applied combined heat and darkness and extended darkness to a panel of ~ 300 Arabidopsis accessions to study lipid remodeling under carbon starvation. Natural allelic variation at 3-KETOACYL-COENZYME A SYNTHASE4 (KCS4), a gene encoding for an enzyme involved fatty-acid elongation, underlies a differential accumulation of polyunsaturated triacylglycerols (TAGs) under stress. Ectopic expression in yeast and plants proved that KCS4 is a functional enzyme localized in the ER with specificity for C22 and C24 saturated acyl-CoA. Loss-of-function mutants and transient overexpression *in planta* revealed the role of KCS4 alleles in TAG synthesis and biomass accumulation. The region harboring KCS4 is under high selective pressure. Furthermore, allelic variation at KCS4 correlated with environmental parameters from the locales of Arabidopsis accessions. Our results provide evidence that KCS4 plays a decisive role in the subsequent fate of fatty acids released from chloroplast-membrane lipids under carbon starvation. This work sheds light on both plant response mechanisms to abiotic stress and the evolutionary events shaping the lipidome under carbon starvation.

Introduction

Plant metabolism profoundly influences or even co-ordinates signaling, physiological, and defense responses. When the prevailing environment is adverse, biosynthesis, concentration, transport, and storage of primary and secondary metabolites are affected, in a stress dependent manner. Metabolic responses to abiotic stress involve fine adjustments in carbohydrate, amino acid, amine and lipid pathways. Proper activation of early metabolic responses helps cells restore chemical and energetic imbalances imposed by the stress and is crucial to acclimation and survival (Fraire-Velázquez and Balderas-Hernández, 2013).

Plant metabolism has been investigated by genome-wide association studies (GWAS), and the genetic determinants of key metabolic traits have been successfully characterized (i.e. primary and secondary metabolites and enzyme activities) (Wu et al., 2018, 2016; Fusari et al., 2017). Regarding lipid metabolism, a number of GWAS have been reported, for instance in Arabidopsis, maize, coffee, and canola, resulting in the identification of new enzymes and regulators (Riedelsheimer et al., 2013; Li et al., 2019; Sant'Ana et al., 2018; Gacek et al., 2017). These studies focused on lipid levels under optimal growth conditions. However, accumulation of lipids is highly affected by fluctuations in the environmental conditions, such as light, temperature and nutrient availability (Burgos et al., 2011; Szymanski et al., 2014; Caldana et al., 2011). A classic example involves compensation for the decreased membrane fluidity under cold stress (Welti et al., 2002). Moreover, adaptation to a high temperature has been associated with an increase in the relative content of digalactosyldiacylglycerol (DGDG) and the ratio of DGDG to monogalactosyldiacylglycerol (MGDG), as well as a moderate increase in fatty-acyl saturation of plant lipids (Han, 2016).

In plants, starch, the major source of energy in the dark, is degraded linearly according to the duration of the previous night (Graf and Smith, 2011). Therefore, plants subjected to a sudden extended night (dark stress) experience carbon starvation. Under these conditions, polyunsaturated fatty acids (FA) released from membrane lipids are used as an alternative substrate for respiration via β-oxidation. Free fatty acids (FFAs) have detergent-like properties and are often sequestered into triacylglycerols (TAGs). TAG synthesis and lipid-droplet formation sometimes constitute a cellular response to lipotoxicity. This is especially true for polyunsaturated fatty acid (PUFA) species because they contain multiple double bonds and are liable to production of reactive oxygen species (ROS). It has been shown that the process of FFA sequestration into TAGs protects the cell from ROS

generated during PUFA peroxidation (Fan et al., 2017). Major changes in lipidomic composition
under stress are accompanied by a remarkable remodeling of gene expression, both at the level of
whole metabolic pathways, but also involving activation of specific stress-induced
isozymes(Szymanski et al., 2014). All these observations indicate that only by causing a perturbation
of the metabolic homeostasis are GWAS likely to capture genes that evolved to stand at critical
branch points in the regulation of the lipidome under natural fluctuating environments.

Here, we performed GWAS using lipidomic data obtained in three different environments: control,
combined heat and darkness, and extended darkness. We observed that many associations were
detected in specific conditions. The locus harboring *KCS4*, an as yet uncharacterized gene encoding
for a *3-KETOACYL-COENZYME A SYNTHASE* (Joubès et al., 2008), was strongly associated with a high
number of polyunsaturated TAGs in stress conditions, but was not detected in control condition.
Thus, *KCS4* association is driven by carbon starvation. Using loss-of-function mutants and ectopic
expression in yeast and plants we explored the biochemical properties of *KCS4* and validated its role
in polyunsaturated TAG metabolism. Taken together, we place a model for *KCS4* function, where
KCS4 acts as a regulatory branch point in the fate of saturated FAs, directing them either to the very-
long chain fatty acid pathway (VLCFA) or to TAG. Two *KCS4* alleles have differential capacity to
process saturated FA, resulting in higher levels of polyunsaturated TAGs in accessions carrying the
strong allele. In fully exploiting the genetic data available for Arabidopsis, this work sheds light on
the evolutionary events shaping the lipidome and further highlights the importance of lipid
remodeling in plant growth.

Results

Plasticity in Arabidopsis lipid metabolism under different environmental conditions

In order to investigate the genetic regulation of lipid biosynthesis in Arabidopsis, we conducted LC–
MS-based lipidomic analysis of 301 and 309 Arabidopsis accessions grown in two environmental
conditions: control (21/16°C in 16/8h light/dark cycle, termed CHD) and stress (heat 32°C + darkness
for 24 h, termed HD), respectively. HD was selected as it has previously been shown to have a strong
effect on the lipidome (Caldana et al., 2011). The mapping population was phenotyped for a total of
98 and 109 glycerolipids in CHD and HD, respectively (Supplementary Table 1).

Principal component analysis (PCA) of lipid data clearly separates the natural ecotypes into two
different groups according to the two environmental conditions tested (Supplementary Figure 1a).
Furthermore, differences in the lipid status between CHD and HD samples showed that TAGs were
strongly accumulated while MGDGs and DGDGs were mostly decreased under stress (Supplementary
Figure 1b). In addition, there is substantial positive correlation between lipid levels from a given lipid
class, suggesting coordinated regulation at the level of lipid classes (Supplementary Figure 1c).
Notably, TAGs showed the highest variation across accessions for both stress and control conditions,
with many species falling in the range of >10-fold difference (Supplementary Figure 1d).

Genetic basis underlying Arabidopsis lipid metabolism

Lipid intensities from CHD and HD and the 250K SNPchip(Horton et al., 2012) were used to perform
two independent genome-wide association studies (GWAS) for the identification of lipid quantitative
trait loci (QTL). The GWAS revealed 93 and 544 SNP–trait associations in control and stress
conditions, respectively, at a genome-wide significance level of LOD ≥ 5.3 (Supplementary Table 2).
These SNP–trait associations further grouped into 51 and 66 QTL for CHD and HD conditions,
respectively. In total, only five QTL were shared between CHD and HD, revealing the great plasticity
of the lipidome in response to different environmental conditions (Supplementary Table 3).

Regarding functional annotation of candidate genes, we mapped 12 and 22 genes putatively
involved in lipid metabolism for control and stress condition, respectively (Supplementary Table 3,
Acyl-Lipid Metabolism database (Li-Beisson et al., 2010) http://aralip.plantbiology.msu.edu/). After
filtering for robust associations co-localizing for two or more traits, four QTL harbored eight lipid-
genes (Figure 1a), including a *LIPASE CLASS 3* (AT1G06250), two *ACYL-COA OXIDASE* (*ACX3*:
AT1G06290 and *ACX6*: AT1G06310), two *FATTY ACID DESATURASE* (*CER17*: AT1G06350 and
FAD2:AT3G12120) and a *LYSOPHOSPHOLIPASE* (AT5G20060) (Supplementary Table 3, Figure 1a).

137 A QTL harboring an enzyme involved in fatty acid elongation has major impact on TAG levels under
138 heat and dark stress

Remarkably, 22 TAGs co-localized to a single QTL on chromosome 1, harboring *3-KETOACYL-*
COENZYME A SYNTHASE4 (*KCS4*, AT1G19440, Figure 1a). This QTL was not found in control
conditions, and the lead SNP in the locus (m11481) co-localized with LOD ≥ 8 (Bonferroni corrected p
< 0.05) for 16 of the 22 associated TAGs (e.g. Figure 1b). An additional 33 genes mapped on the QTL,
spanning 107,318 bp (Supplementary Table 3). However, with the exception of *KCS4,* none of the
others showed any homology to proteins known to be involved in lipid metabolism. *KCS4* belongs to
a gene family involved in the elongation of VLCFA. Twenty-one *KCS* genes have been previously
identified in the Arabidopsis genome. The *KCS* family encodes for enzymes involved in the first and
often described as rate-limiting step of fatty–acid elongation (FAE) (Blacklock and Jaworski, 2006;
Joubès et al., 2008). KCS4's closest homologues are: KCS9 (78% aa identity), involved in the
elongation of C22 to C24 acyl-CoAs (Kim et al., 2013); KCS17 (72% aa identity); and KCS18 (64% aa
identity), involved in elongating C18 acyl-CoAs to C20 and C22 in seeds and shown to drive the
natural variation in the abundance of VLCFAs in this organ (Patrick and Colyvas, 2014; Rossak et al.,
2001). However, KCS4 specificity and function have not been characterized so far.

TAGs associated with the *KCS4* QTL were mostly polyunsaturated (e.g. 52:6, 52:7, 54:6, 54:8, 54:9,
56:6) and correlated positively with each other, grouping together in a single very-well defined
cluster (Figure 1c).

To identify the alleles involved in TAG variation under HD, we constructed haplotypes considering
the four SNPs from *KCS4* (m11502, m11503, m11504, m11505). The population divided into nine
non-unique haplotypes, which were therefore, further considered as being putatively involved in the
QTL variation. Mean levels of TAG 54:9 varied significantly among haplotypes (Figure 1d).
Furthermore, m11503 was identified as a non-synonymous SNP (nsSNP). In the majority of
accessions, SNP m11503 encodes for a methionine [hereafter *KCS4*(Met)]. Accessions carrying this
allele have higher levels of TAG in the stress condition than accessions carrying the minor allele,
which encodes for a threonine [hereafter *KCS4*(Thr)] (Figure 1e)*.* These results suggest that the
nsSNP in *KCS4* is a causal mutation underlying polyunsaturated TAG variation in Arabidopsis, under
stress conditions.

166 KCS4 associates with polyunsaturated TAGs in extended darkness

Thus far, we found that *KCS4* associates with polyunsaturated TAGs in a combined heat and dark
treatment. In prolonged darkness, starch is prematurely exhausted and plants are carbon
starved(Stitt and Zeeman, 2012). Therefore, we determined whether *KCS4* associates with TAGs,
when only extended darkness is applied.

For this purpose, we conducted three additional independent lipid GWAS experiments: control (CD),
3 days (3D) extended darkness, and 6 days (6D) extended darkness (Supplementary Table 1). The
GWAS at a genome-wide significance level of LOD ≥ 5.3 resulted in 230, 255 and 342 SNP–trait
associations grouped in 73, 81, and 70 QTL for CD, 3D, and 6D, respectively (Supplementary Table 2,

Supplementary Table 3). The locus harboring *KCS4* associated strongly in 3D and 6D with 8 and 13
TAGs, respectively. Lead SNP and other features of the association matched with GWAS results from
the HD experiment (Supplementary Figure 2). Therefore, darkness alone is enough to trigger the
association of *KCS4* with polyunsaturated TAGs.

Dissection of *KCS4* alleles involved in TAG variation, pattern of linkage disequilibrium and
signatures of selection

We next mined the full sequence information available for 149 accessions from the GWAS
population (http://signal.salk.edu/atg1001/3.0/gebrowser.php), for 80 kb around SNP m11481 on
chromosome 1. The sequence alignment (Supplementary File 1) was used to build a SNP matrix
(Supplementary Table 4) to perform GWAS with more SNPs than those included in the previous
experiments using the SNPchip(Horton et al., 2012). We analyzed a total of 1,082 SNPs and short
insertion-deletions, in addition to the 131 SNPs previously tested in this region. These analyses aim
to discard genetic heterogeneity among other genes in the locus, analyze the pattern of linkage
disequilibrium (LD) in the region, determine whether other SNPs in *KCS4* are additionally involved in
the variation, and evaluate signatures of selection. The results are shown in Figure 2, exemplified for
TAG 54:9. According to the *KCS4* gene model (Figure 2a), we gf 35 additional SNPs in *KCS4* apart from
the 4 SNPs in the SNPchip (19 in the promoter, two in the 5'UTR, 13 in the coding region, and one in
the 3'UTR; Supplementary Table 5). Overall, fewer TAGs with lower association values co-localized
for 3D than for HD, mimicking GWAS results obtained using the 250K SNPchip (Supplementary Table
5, Figure 2b). This suggests that there is an additive or synergistic effect of both heat and dark
stresses in the regulation of TAGs mediated by *KCS4*. The lead SNP using resequencing information
was a polymorphism not tested before (rs21933), but in high LD with m11481 (r^2 =0.73, p << 0.001).
In addition, a number of polymorphisms in the upstream region of *KCS4,* not tested in the SNPchip,
were identified as being significant, pointing to a putative combined regulation at the promoter
region mediated by rs39451, rs39499 and m11502 and at the coding region mediated by the nsSNP
m11503 (Figure 2a). Furthermore, several SNPs in the *KCS4* coding region surprisingly did not
associate with the QTL on chromosome 1 (Figure 2b).

The pattern of LD showed that all SNPs associated to the QTL in chromosome 1, are in high LD with
each other and in high LD with the lead SNPs rs21933 and m11481 (r^2 > 0.2, p < 0.001, Figure 2c).
The remaining SNPs in the *KCS4* coding region are not in LD either with the lead SNPs or with the
nsSNP m11503 in the *KCS4* coding region. This result suggests that these mutations may have
appeared in a different time during evolution or they may have accumulated later, as a consequence
of specific recombination, to increase allele frequency at other SNP positions. To evaluate signatures
of selection, we tested Tajima's D for the 80 kb around m11481 (Figure 2d). Tajima's D reached
significantly negative values along the 80 kb, particularly around SNPs significantly associated in the
QTL: rs21933, m11481, rs39451, rs39499, m11502, m11503. This result indicates that the region is
under a high selective pressure.

KCS4 functional validation using knockout mutants in Arabidopsis and transient overexpression in
Nicotiana benthamiana

To validate the role of *KCS4* alleles in TAG variation under HD stress, we selected six accessions:
three carrying *KCS4*(Met) and three carrying *KCS4*(Thr). Selection of these accessions was based on
TAG levels measured in the HD experiment. Knockout (KO) lines were obtained through CRISPR-Cas9
by introducing a 57/58–bp deletion at position +18 from the ATG (Supplementary File 2). This
deletion introduced a premature stop codon resulting in a truncated protein of 16 aa compared to
the wild-type version of 516 aa. Lines were grown under CHD or HD conditions, and harvested in two
independent experiments (Exp1, Exp2; Supplementary Table 6). Since natural variation is detected at

a population level, TAGs were analyzed by comparing the average behavior of *kcs4* and wild-type
KCS4 accessions, according to the allele carried (Figure 3). Accessions carrying *KCS4*(Met) presented–
on average–significantly higher polyunsaturated TAG levels under HD conditions than accessions
carrying *KCS4*(Thr). *Kcs4*(Met) and *kcs4*(Thr) did not show any significant difference compared to
KCS4(Met) and *KCS4*(Thr), respectively (Figure 3a/3b). The fact that knocking out *KCS4* does not
seem to produce an effect on TAG levels could be due to a feedback loop activated on other
members of the *KCS* family to compensate for KSC4 activity, when there is complete loss of the *KCS4*
transcript.

On the other hand, transient expression of At*KCS4*(Met) in *N. benthamiana* leaves shows
significantly higher levels of polyunsaturated TAGs for classes 52, 54, and 56 compared to control
plants (Figure 3c). Conversely, TAGs with one or a few unsaturated bonds tend to be higher in
control plants. These results show that the transient expression of At*KCS4*(Met) changes the TAG
profile in *N. benthamiana*. Saturated FAs are channeled to VLCFA elongation, tipping the balance to
a higher polyunsaturated-to-saturated-FA ratio and driving the production of polyunsaturated TAGs
at the expense of saturated TAGs.

Transcriptional regulation of *KCS4* in Arabidopsis

Several SNPs in the promoter region induced us to attempt to identify the transcriptional regulators
of *KCS4* in Arabidopsis. We analyzed 1 kb upstream of the transcription start site for the known
transcription factor binding sites using the DAP-Seq database (O'Malley et al., 2016). We found
several transcription factor (TF) families belonging to land plants that could likely bind to the *KCS4*
promoter region, indicating that *KCS4* expression might be controlled under several regulatory
processes (Figure 4a).

We furthered our analysis by looking at the core binding sites of the highly enriched TF families that
contained binding motifs across SNPs in the promoter region of *KCS4* (rs38889, rs39451, rs39499
and m11502). The top-enriched DOF family (DNA-binding one zinc finger) does not have a binding
site within the SNP region, but in other regions of the promoter (Figure 4b). Similarly, the NAC and
WRKY TF families bind to non-polymorphic regions in the *KCS4* promoter, and MYB TF binds near a
SNP but in the coding region. Interestingly, HSF (heat shock factor), the second highly enriched TF
family has a core binding motif (heat shock element: 5'nnGnAnnTnCtn 3') within SNP m11502 in the
promoter region.

Next, we performed an electrophoretic mobility shift assay (EMSA) to assess the physical interaction
of Heat Shock Factor A2 (HSFA2) with the KCS4 promoter sequence. Additionally, we tested if alleles
(C/T) at SNP m11502 influence the binding affinity. *HSFA2*, a well-studied HSF family member, has
been shown to bind to the heat shock element in Arabidopsis (Lämke et al., 2016). As shown in
Figure 4c, HSFA2-GST fusion protein bound to the 5'-DY682-labeled *KCS4* promoter fragment *in vitro*
with the C allele at m11502, resulting in a retardation band on the gel (Figure 4c, lane 2) compared
to the free probe (lane 1). Interaction between HSFA2 and the *KCS4* promoter region containing the
binding site appears to be specific, as the addition of an excessive unlabeled competitor (same
sequence, 200x more) significantly reduced the binding to the labeled probe (Figure 4c, lane 3).
Finally, we tested a competitor sequence having the alternative allele at m11502 (T). The latter
reduced the binding compared to the labeled probe (Figure 4c, lane 6), suggesting that the T allele at
m11502 determines a stronger binding of HSF2A to the *KCS4* promoter region. Overall, this indicates
that natural variation at the promoter region could contribute to the final effect and function of the
different *KCS4* alleles.

Furthermore, we analyzed natural variation in transcript levels of *KCS4* for thevCHD and HD
conditions in the complete GWAS panel (Figure 4d). *KCS4* transcripts are significantly lower in HD
compared to CHD. This correlates significantly negatively with highly unsaturated TAG levels (r^2 = -
0.66, p < 0.001), which increased in HD (e.g. Figure 4e, TAG 54:9). In HD, *KCS4* transcript levels are
not significantly different for accessions carrying different alleles at m11502 (Figure 4e).

To gain further insight on the regulation of *KCS4* transcript, we performed expression QTL (eQTL)
analysis using *KCS4* expression data for the complete GWAS population in CHD and HD conditions
(Supplementary Table 7). We identified 29 eQTL for a LOD ranging from 5 to 6. We detected a QTL
harboring *MYB96* (AT5G62470) in the CHD condition. It was shown that *MYB96* acts as a
transcriptional activator of the *KCS* genes(Seo et al., 2011). Interestingly, the *ACX3* (AT1G06290) and
ACX6 (AT1G06310) genes were also found associated with *KCS4* transcript levels in HD
(Supplementary Table 7). The first step of peroxisomal FA β-oxidation is catalyzed by ACX
enzymes(Khan et al., 2012; Eastmond et al., 2000). ACX3 has specificity for medium-chain FA, and its
function has also been linked to the indole-3-butyric acid (IBA) to indole-3-acetic acid (IAA) β-
oxidation in the peroxisome (Adham et al., 2005). This result might indicate a regulatory feedback
among IAA response to stress, FA degradation and VLCFA synthesis mediated by *ACX* genes and *KCS4*
transcript.

Expression patterns of the KCS gene family in eight environmental conditions

To evaluate the effect of heat and darkness on the expression of *KCS4* and to compare expression
patterns in different environmental conditions across the *KCS* family, we analyzed the time-resolved
response of Arabidopsis Col-0 accession towards light and temperature for 16 of the 21 gene
members using previously obtained data (Caldana et al., 2011). Because of the complexity of the
response, we focus on the last time-point, i.e. 24 h after treatment (Figure 4f). Most *KCS* members,
including *KCS4* are upregulated under light conditions and downregulated in darkness, irrespective
of the temperature. However, *KCS8*, *KCS12*, *KCS16*, *KCS18*, and *KCS21* showed an opposite behavior.
KCS4 transcript levels are downregulated both under darkness and under HD, but they are much
lower in HD, reinforcing the idea of a synergistic effect between light and temperature stress in the
KCS4 response. In addition, *KCS5*, *KCS9* and *KCS20* showed a similar transcriptional response as *KCS4*
across several environmental stimuli (Figure 4f).

KCS4 shows specificity for elongation of VLCFA up to 26-carbon chains

KCS4 shows sequences homology to the remaining 20 members of the Arabidopsis *KCS* multigene
family(Joubès et al., 2008). As stated before, KCS enzymes catalyze the first rate-limiting step in the
VLCFA elongation, and determine the substrate specificity.

To evaluate if KCS4 has a very-long-chain 3-ketoacyl-CoA synthase activity and to investigate its
substrate specificity, we heterologously expressed *AtKCS4*(Met) in yeast and evaluated the VLCFA
profile. The strain expressing *AtKCS4* synthesized significantly higher levels of VLCFA from C20 to C26
compared to the strain transformed with an empty vector (Figure 5a). Because yeast has its own
well-described machinery for VLCFA synthesis, we further expressed *AtKCS4* in a yeast strain that
lacks the *ELO3* gene encoding elongase (Δ*elo3,* Figure 5b). Because the yeast ELO3 elongase is
essential for the elongation of VLCFA from C22 to C24 and C26 (Han et al., 2002), the Δ*elo3* mutant
showed high accumulation of C20 and C22 VLCFA. The Δ*elo3* mutant expressing *AtKCS4(Met)*
accumulated substantial amounts of C24 and C26 VLCFA, confirming that KCS4 is involved in the
elongation of VLCFAs from C22 to C24 and from C24 to C26 (Figure 5b). We also analyzed *KCS9*
heterologous expression in yeast (Figure 5b). *KCS9* is the closest *KCS4* homolog and its specificity is
to elongate VLCFAs from C22 to C24 (Kim et al., 2013). The Δ*elo3* mutant expressing *KCS9*, as

expected, showed a peak in C24 accumulation. These results suggest that KCS4 has a differential activity compared to KCS9, pushing further the elongation of VLCFAs up to C26.

Transient expression of *AtKCS4* in *N. benthamiana* leaves showed a significant decrease of C20 and C22 VLCFAs and a significant increase of VLCFAs from C26 up to C30 in comparison to the control (Figure 5c). The elongation of VLCFAs from C26 to C30 in *N. benthamiana* might be the result of the action of the native elongase complex due to increased availability of C26 when *KCS4* is transiently expressed.

KCS4 is localized in the endoplasmic reticulum (ER)

In plants, the elongase complex is localized in the ER (Joubès et al., 2008). To monitor KCS4 localization we fused YFP to the C-terminal end of AtKCS4 and visualized it with confocal microscopy (Figure 5d).

AtKCS4-YFP was found to label a polygonal and tubular network characteristic of the endoplasmic reticulum (ER), in agreement with previous results shown for other KCS family members(Joubès et al., 2008).

Biomass is affected by lipid rearrangement mediated by KCS4 in stress conditions

It has been demonstrated that a mild reduction in VLCFA content improve cell proliferation and shoot growth (Nobusawa et al., 2013). To investigate if knocking out *KCS4* has such an effect, we compared biomass of *kcs4* mutants and their respective WT for the accessions Pro-0 [*KCS4*(Met)] and Sh-0 [*KCS4*(Thr)].

The *kcs4* lines, grew significantly bigger than their WT counterparts, indicating that biomass is negatively correlated with KCS4 activity (Figure 6).

Phylogenetic signal of the lipidome and correlation with climatic and geographical conditions

To test if there is correlation between lipid profiles and genetic distance (a proxy for phylogeny), K statistics and empirical p-values were calculated for all the measured lipid features in control (CHD) and stress (HD) conditions (Blomberg et al., 2003). The results indicate a correlation between genetic distance and the similarity of lipidomic profiles. Lipids exhibiting a significant phylogenetic signal in CHD are enriched in MGDGs ($p \leq 0.001$) while in HD we observed enrichment in TAGs ($p \leq 0.05$). Five of the six TAGs with a significant phylogenetic signal are polyunsaturated species associated with the *KCS4* QTL (Supplementary Figure 3).

In addition, climate conditions from the geographical origins of accessions (Fick and Hijmans, 2017) were also analyzed to identify putative correlations with lipidomic profiles. We used a lasso regularized linear model to predict each climate parameter from the lipidomic profiles. In result, we estimated the prediction power for each best-fitting model, and the lipids, being the best predictors for the climate parameters. While the CHD condition did not provide significant results, the HD condition highlighted in total 15 significant model fits, five of which gave also significant results in a cross-validation test (Supplementary Figure 4). All of these five significant variables are related to temperature. In total, six "climate-predictive lipids" were also significantly associated with *KCS4*, with TAG 58:6, TAG 60:6, and TAG 56:8 being linked to the temperature in the driest and the coldest quarter of the year.

Finally, cluster analysis was performed for climate parameters and TAG levels, by grouping accessions according to *KCS4* haplotypes (m11502-m11503: CC, CT, TT, TC), and significant differences between mean values for haplotypes were tested using non-parametric ANOVA. Eight climate parameters plus latitude and longitude differed significantly between haplotypes ($p < 0.05$,

353 Figure 7a). Moreover, five of them co-clustered with TAGs associated with *KCS4*, four of them
354 related to precipitation and one to temperature (isothermality). The "TT" haplotype in most cases,
355 presented the lowest value for these parameters, suggesting that the allelic effect of these two SNPs
356 is opposite for climate variables (Figure 7b).

Discussion

Recent years have witnessed the successful application of metabolic GWAS (Luo, 2015). In lipids, the
effort has focused more on dissecting the genetic architecture of oil biosynthesis (Correa et al.,
2020). Here, we focus on glycerolipid profiles of ~ 300 Arabidopsis natural accessions grown under
different environmental conditions. Our GWAS exposed the high plasticity of the Arabidopsis
genome allowing the identification of genes involved in the regulation of lipid metabolism, in an
environment-dependent manner (Figure 1a).

Lipid-based GWAS in control conditions showed several mild-strength associations, similar to the
pattern obtained for primary metabolites (Wen et al., 2015; Wu et al., 2016), which are controlled by
a large number of small-effect loci. This could be explained by the fact that both lipids and primary
metabolites are essential for the survival of the cell and thus, do not show on/off phenotypes. This is
different from natural variation in secondary metabolites, which are controlled, to a large extent, by
major large-effect loci (Wu et al., 2018; Chan et al., 2011; Wen et al., 2014; Matsuda et al., 2012).

In our study, applying stress resulted in a strong perturbation of lipid homeostasis. This resulted in
the identification of a large-effect QTL at the *KCS4* gene. *KCS4* associated with several
polyunsaturated TAGs specifically under stress conditions (HD, 3D and 6D) in a highly robust manner
(Figure 1b, Supplementary Figure 2b). Under HD, all TAGs mapping to *KCS4* are higher than under
CHD. In contrast, under 3D there is a strong reduction in polyunsaturated TAGs in comparison to CD.
Under 6D, levels are similar to the TAG values found under CD. Irrespective of this, accessions
carrying *KCS4*(Met) always presented higher levels of polyunsaturated TAGs than accessions carrying
KCS4(Thr). Polyunsaturated TAGs that mapped to *KCS4* clustered together and negatively correlated
to saturated TAGs, further illustrating the role of *KCS4* in the specific regulation of polyunsaturated
TAGs (Figure 1c).

Repression of several KCS family members has been shown to occur during darkness due to the
activation of a TF that downregulates the wax biosynthetic pathway(Go et al., 2014; Kim et al.,
2018). We, too, observed downregulation of a number of *KCSs* under darkness alone, and under
combined HD (Figure 4f), including *KCS4* (Figure 4d). These findings are in line with the notion that
VLCFA elongation slows down upon stress in order to re-allocate carbon resources under carbon-
limiting conditions.

So far, KCS4 enzymatic characterization has not yet been achieved. Our experiments indicate that
KCS4 is a functional enzyme, localized in the ER, with substrate specificity for VLCFAs of C22 and C24
length, and has the ability to elongate VLCFAs to C24 and up to C26 (Figure 5). Moreover, the results
from ectopic expression in yeast and plants confirmed that KCS4 has specificity for elongation of
saturated FAs (Figure 5), in agreement with previous findings that shows that elongase-condensing
enzymes are mostly active with saturated FA (Blacklock and Jaworski, 2006).

Under HD, differences in TAG levels for accessions carrying *KCS4* opposite alleles [KCS4(Met) vs.
KCS4(Thr)] become more significant as the number of double bonds in the TAGs increases (Figure
3a). However, TAG levels are not significantly different when comparing knock-outs to their wild-
type counterparts. Limitations in the study of knock-out mutants have been previously pointed out.
For instance, the phenotype can depend on the context and a change in either the genetic or the

environmental background can amplify or remove the effect (Tonsor et al., 2005). In addition, sometimes effects are not evident when analyzing single mutants, particularly if there are gene families encoding for the same or very similar enzymatic activities. For example, in studies of auxin conjugates, IAA showed a reduction only when triple amidohydrolase mutants were analyzed (Ludwig-Müller, 2011). *KCS4* is one of 21 genes encoding for KCS activity (Guo et al., 2016; Joubès et al., 2008). Despite each KCS having specificity for VLCFAs with different acyl-chain lengths, there is some redundancy and overlap (Blacklock and Jaworski, 2006). This redundancy is also observed in their expression patterns (Figure 4f).

During plant evolution, the *KCS* family began with a single gene in algae and evolved via numerous gene duplications into a 21-member gene family in Arabidopsis(Guo et al., 2016). Analysis of LD and Tajima's D parameters in the region harboring *KCS4* showed that diversity is limited to two major haplotypes and that the region is under strong selective pressure (Figure 2). As *KCS4* is involved in TAG regulation under conditions where carbon reserves are exhausted, it might be possible that *KCS4* has been targeted for natural selection to enhance adaptation in stressful environments. In nature, 24 h of darkness does not occur, but carbon starvation is also observed when plants are exposed to very-limited light periods in regions with high amplitudes of day-length. In agreement with an adaptative role of *KCS4* to environmental stresses, the geographical origin of the accessions (i.e. latitude) correlated with *KCS4* haplotypes (Figure 7). Together, these analyses indicate that polymorphism variation at *KCS4* is important for adaptation in different climatic zones by adjustment of lipid metabolism.

To summarize our findings, we present a model of lipid remodeling under heat and dark stress in Arabidopsis (Figure 8). In an event of sudden extended darkness, plants become carbon starved (Stitt and Zeeman, 2012). It has been shown that increasing night temperature accelerates enzyme activities exhausting carbon resources prematurely (Pilkington et al., 2015). In this case, FAs are used as alternative substrates for respiration via β-oxidation (Fan et al., 2014). In the proposed model, darkness induces the predominant response within the combined stress, blocking *de novo* FA synthesis (FAS) and producing considerable membrane-lipid remodeling. We observed decreased levels of MGDGs and DGDGs across accessions, as previously shown (Burgos et al., 2011). Under carbon starvation, FAs, mostly 16:3 and 18:3, are released from galactolipids by lipases (Fan et al., 2017; Higashi et al., 2015). FAs are then exported to the ER, where KCS4 is localized and acts as a branch point in the fate of FAs, directing the saturated ones to the very-long-chain fatty-acid pathway (VLCFA). Two *KCS4* alleles have differential capacity to allocate saturated FAs into the VLCFA pathway, with a major -more efficient- allele, *KCS4*(Met), and a minor -weaker- allele, *KCS4*(Thr). Polyunsaturated TAG levels are, therefore, higher in *KCS4*(Met) accessions comparing to *KCS4*(Thr) accessions, as the result of a rise in the ratio of polyunsaturated-to-saturated FAs that proceed to TAG formation. This effect of *KCS4*(Met) on TAG levels is only observed under stress conditions, when there is an increased amount of free-polyunsaturated fatty acids coming from membrane lipids, and when it necessary to sequestered them into TAGs, to protect the cell from the free-fatty-acid-toxicity induced damage (Kao et al., 2018). A number of additional regulatory points have been identified to influence VLCFA production, and more general lipid remodeling under HD. For instance, as the wax pathways is downregulated due to the activation of DEWAX TF under darkness (Go et al., 2014; Kim et al., 2018), VLCFA-CoA could directly serve as a source of carbon, and undergo degradation in the peroxisome. In addition, *KCS4* transcripts mapped to *ACX3* and *ACX6*, indicating a genetic interaction between these two loci. As ACXs are key enzymes for FA degradation, and they have been also implicated in the IBA to IAA conversion in the peroxisome, this interaction might help both to adjust the energy demand of the cell under carbon starvation and to activate auxin responses against stress.

In conclusion, our study demonstrates that lipidomic-GWAS performed under stress conditions is a powerful and unbiased tool for shedding light on the genetic control of lipid metabolism. We identified a QTL to which lipids mapped in an environment-specific fashion, thus illustrating the plasticity of the genome in the regulation of lipid metabolism in changing environments. This approach fleshed out the fundamental role that KCS4 has in FA re-channeling under stress and proved to be powerful in unraveling the genetic regulation of complex phenotypes.

Methods

Plant material

The GWA mapping population comprised a total of 330 *Arabidopsis thaliana* natural accessions belonging to the HapMap panel (Horton et al., 2012). This panel was selected because the accessions maximize diversity and minimize redundancy and close family relatedness(Baxter et al., 2010).

Experimental design

Accessions or mutant lines were grown in soil (potting compost) in short days (8 h light) for four weeks, then transferred to long days (16 h light) for an additional period of two weeks. Control plants were harvested immediately and stressed plants were subjected to the treatment and harvested right after it.

In control conditions (for heat/dark experiment: CHD, for dark experiment: CD), plants were grown in long days (16h light, 8 h dark), temperature was kept at 21/16°C (day and night, respectively), light intensity at 150 μE m^{-2} sec^{-1}, humidity 75%. In the heat and dark experiment (HD), plants were grown like the plants in CHD for six weeks, then subjected to dark and 32°C continuously for 24 h, and then harvested. In the dark treatment, plants were grown like the plants in CD for six weeks and then transferred to continuous darkness either for 72 h (3D) or 144 h (6D). Plants from HD, 3D, 6D were harvested 24 h, 72 h, and 144 h after the beginning of the treatment, respectively. Between three and six plants from each accession/line were collected for each condition tested.

Targeted lipid profiling by LC–MS and data acquisition

Lipid extraction and measurement from Arabidopsis leaves were performed as described previously (Hummel et al., 2011). In brief, dried organic phase was measured using Waters Acquity ultra-performance liquid chromatography system (Waters, http://www.waters.com) coupled to Fourier transform mass spectrometry (UPLC–FT–MS) in positive ionization mode. Analysis and processing of raw MS data were done with REFINER MS® 10.0 (GeneData, http://www.genedata.com). Workflow included peak detection, retention time alignment and removal of chemical noise and isotopic peaks from the MS data. Obtained mass features characterized by specific peak ID, retention time, m/z values and intensity were further processed using custom scripts in R (R Core Team, 2019). Clusters with mean of signal intensities lower than 50000 were removed and only peaks present in at least 70% of the samples were kept for further analysis. Peak intensities were normalized by the day of measurement and median and subsequently log$_2$ transformed. After that, obtained molecular features were queried against a lipid database for annotation. The in-house database used includes 219 lipid species of the following classes: diacylglycerols (DAGs), digalactosyldiacylglycerols (DGDGs), monogalactosyldiacylglycerols (MGDGs), phosphatidylcholines (PCs), phosphatidylethanolamines (PEs) and triacylglycerols (TAGs). This was carried out by comparing their retention times and exact masses against those of the reference compounds, allowing maximal deviations of 0.1 minutes and 10 ppm. Identified lipids were confirmed by manual verification of the chromatograms using XCalibur (Version 3.0, Thermo-Fisher, Bremen, Germany).

General statistical and multivariate analysis of lipidomic data

To calculate the correlation between lipids, Pearson correlation was used. The correlation plots and heatmaps were created using the package pheatmap (Raivo Kolde, 2019). The lipids were clustered using complete-linkage clustering. Principal component analysis (PCA) was obtained from the correlation matrix of lipidomic data (CHD and HD together) using the pcaMethod (Stacklies et al., 2007) package.

To detect the fold change in lipid-feature levels across all accessions for each lipid feature, fold change was calculated by dividing the average of the five highest intensities measured in a given accession by the average of the five lowest intensities, A) for all annotated lipids (N_{CHD} = 98, N_{HD} = 109), B) only for TAGs (N_{CHD} = 30, N_{HD} = 41), C) for lipid classes other than TAGs (N_{CHD} = 68, N_{HD} = 68).

GWAS analysis

Data acquisition for GWAS, mapping and locus identification were performed as described previously (Wu et al., 2016; Fusari et al., 2017). Genome-wide association analysis (GWAS) was performed using a compressed mixed linear model (MLM) implemented in the GAPIT (Lipka et al., 2012) package. The 109 (HD), 98 (CHD), 80 (3D), 109 (6D), and 122 (CD) lipid features were used as phenotypes (Supplementary Table 1), whereas a set of 214,051 SNPs was used as genotypic data (250K SNPchip). A total of three principal components were included in the MLM to account for population structure and the SNP fraction considered to perform PCA was set to 0.1 to avoid excessive computations. Kinship matrix and other parameters were set to default values.

Additionally, we performed GWAS using full genome sequence from a section of chromosome 1. Shortly, sequences for 80 kb around *KCS4* (AT1G19440, TAIR10 position: 6689119 - 6769118) were obtained from the Arabidopsis 1001 Genomes project (http://signal.salk.edu/atg1001/3.0/gebrowser.php, 162 accessions). The alignment was performed using the default routine implemented in MAFFT (Katoh et al., 2019) with a final manual inspection to discard alignment problems due to big gaps or missing data (Supplementary file 1). For nine accessions, two sequences were available. The sequences included further in the analysis were selected based on agreement of alleles with the SNPchip data and/or on % of non-missing data (≥ 90%). Final SNP matrix, obtained by filtering for minor allele frequency ≥ 5%, contained 1,213 SNPs and indels (Supplementary Table 4). This matrix was used as the genotypic data. Population structure and cryptic relationships among accessions were taken into account by including principal components as cofactors and a kinship matrix obtained with SNPs in the 250K SNPchip for the subset of 162 accessions (Supplementary Table 4). Lipid features collected formerly (HD and 3D) Supplementary Table 1) were used as phenotypes. The three data sets (genotype, population structure and phenotypes) matched for 149 accessions in the HD experiment and for 134 accessions in the 3D experiment. MLM was implemented using TASSEL software with the default settings for compressed MLM (Bradbury et al., 2007).

SNP filtering, QTL identification and candidate gene selection

For results obtained using GAPIT package, SNPs associated with lipid species having a p value < 1/N (N=214,051) were extracted. SNPs were assigned to the same QTL if the genomic distance between them was ≤ 10 kb. All genes in a given QTL were taken as putative candidates. Further candidate gene selection for validation was done based on functional annotation or based on previous knowledge.

For results obtained using Tassel software, SNPs were regarded as significantly associated with lipid
traits after setting Bonferroni threshold (α = 0.05/N, N = 1,213 polymorphism tested).

Linkage disequilibrium, nucleotide diversity, and haplotype analysis

Linkage disequilibrium (LD) was computed as the coefficient of correlation between pair of sites (r^2)
using the LDheatmap package(Shin et al., 2006), either with the SNPchip (for 1,300 and 314
accessions) or with the full sequence data (for 149 accessions). For deviations from neutrality,
Tajima's D statistic (Tajima, 1989) was computed as described previously (Fusari et al., 2017).

Haplotypes for *KCS4* were obtained by using SNPchip data considering 1,000 bp upstream the ATG,
the coding region and 1,000 bp downstream the stop codon (SNPs= m11502, m11503, m11504,
m11505). Accessions belonging to the same haplotype were grouped and the haplotype median was
obtained for each lipid feature. To cluster haplotypes, a combination of allele sharing distance and
Ward's minimum variance was used, as described before(Gao and Starmer, 2007; Qiu et al., 2015).
One-way ANOVA followed by Bonferroni correction for multiple comparisons was performed to test
differences between haplotypes (p < 0.05).

Mutant line selection and genotyping

For Arabidopsis CRISPR-Cas9 KO lines, the binary vector containing multiple gRNAs and the Cas9
nuclease were generated based on a classic cloning procedure described previously(Schumacher et
al., 2017). A pair of guideRNAs was used to target the N-terminal coding sequence of *KCS4* using the
spacer sequences indicated in Supplementary Table 8. As background, wild-type accessions carrying
KCS4(Met): Pro-0, Petergof, Per-1, Col-0; and *KCS4*(Thr): Si-0, Bu-8, Sh-0 were chosen based on TAG
levels phenotyped in HD. Mutations were confirmed by PCR and sequencing of *KCS4* using primers
listed in Supplementary Table 8. Sequence contigs and alignment were done using Bioedit (Hall,
1999).

For heterologous expression in yeast and transient expression in *Nicotiana benthamiana, KCS4* and
KCS9 open reading frame was amplified from Arabidopsis flower cDNA using primers listed in
Supplementary Table 8. The corresponding PCR fragments were inserted into the pDONR™221
ENTRY vector using the GATEWAY® recombinational cloning technology (Invitrogen, Darmstadt,
Germany) and subsequently transferred into pK7YWG2, pK7WG2D and pvtLEU DESTINATION vectors
(Karimi et al., 2002; Dittrich-Domergue et al., 2014) by using LR clonase II. All transient heterologous
expressions in *N. benthamiana* were made using the *Agrobacterium tumefaciens* strain GV3101 and
five-week-old plants cultivated in controlled conditions (16 h light photoperiod, 25 °C) (Perraki et al.,
2012). *N. benthamiana* plants were agroinfiltrated on the abaxial side of the leaves and analyzed 2
and 5 days after agroinfiltration for subcellular localization experiments and for overexpression,
respectively.

For yeast experiments, *Saccharomyces cerevisiae* strains INVSc1 [MATa *his3Δ1 leu2 trp1-289 ura3-*
52] and Δ*elo3* [MATa *his3Δ1 leu2 trp1-289 ura3-52 elo3Δ*] were used to express *KCS4 and KCS9*.

qRT-PCR and eQTL analysis

RNA extraction followed by cDNA synthesis and qRT-PCR were performed as described before
(Thirumalaikumar et al., 2018). *ACTIN2* (AT3G18780) was used as a reference gene for *HSFA2*/*KCS4*
transcript analysis in Col0 and *hsfa2* mutant. *RGS1-HXK1 INTERACTING PROTEIN1/RHIP1*
(AT4G26410) was used as reference gene for *KCS4* transcript analysis in CHD and HD for the
complete GWAS population (Czechowski et al., 2005). Primers used to test *KCS4*, *HSFA2* and
reference genes are listed in Supplementary Table 8.

qRT-PCR was performed on samples made out of three biological replicates pooled together. Each
sample was tested in three technical replicates. qRT-PCR was performed on an ABI Prism® 7900 HT
real-time PCR system (Applied Biosystems/Life Technologies, Darmstadt, Germany) in 384-well PCR
plates with a total reaction volume of 5µL (2 µL forward and reverse primer mixture, 0.5 µM each),
0.5 µL cDNA and 2.5 µL Power SYBR® Green-PCR Master Mix (Applied Biosystems/Life Technologies)
using the following cycling program: 50°C for 2 min, 95°C for 5 min, 40 cycles of 95°C for 15 s and
60°C for 60 s, followed by a denaturation step of 95°C for 15 s, 60°C for 15 s, followed by a
continuous temperature increase (0.3°C per s) to 95°C (for 15 s). Steps 5, 6 and 7 were introduced to
record a dissociation or melting curve for each product in order to detect non-specific amplification.
Expression values were calculated by $2^{(-\Delta\Delta Ct)}$ using either *ACTIN2* or *RHIP1* as reference genes. Errors
are given as the lower ($2^{-(\Delta\Delta Ct-SD)}$) and upper ($2^{-(\Delta\Delta Ct+SD)}$) limit of the standard deviation around the
mean.

eQTL analysis was performed using *KCS4* expression data measured in CHD and 24 h after HD for the
complete GWAS population (Supplementary Table 7). ΔCT was used as trait for the mapping and it
was calculated using *RHIP1* as reference gene. The GWAS was performed as described in "GWAS
analysis" section.

EMSA

EMSA reactions were performed as previously described (Thirumalaikumar et al., 2018). Briefly,
HSFA2-GST proteins were prepared as stated before (Puranik et al., 2011). *HSFA2* coding sequence
was PCR-amplified from Arabidopsis heat-stressed cDNA using primers listed in Supplementary Table
8. PCR products were recombined in pDEST24 using the GATEWAY cloning system (Invitrogen).
Recombinant vectors were transformed into *Escherichia coli* Star (DE3) pRARE generated by
transforming the pRARE plasmid isolated from Rosetta (DE3). 5'- labeled with fluorescent dye DY682
and unlabeled *KCS4* promoter regions spanning the SNP position m11502 (C or T allele) were
purchased from Eurofins MWG operon. DNA EMSA reactions were performed using Odyssey
Infrared EMSA kit (Li-COR, Bad Homburg, Germany). Competitor was added at 200x the amount of
probe.

Fatty-acid composition and content analysis for *N. benthamiana and yeast*

For fatty acid methyl esthers (FAME) in *N. benthamiana*, three agroinfiltrated leaf discs were
transferred to tubes containing 1 mL 0.5 M sulfuric acid in methanol containing 2% (v/v)
dimethoxypropane and 20 µg of heptadecanoic acid (C17:0) as internal standard. Transmethylation
was performed at 85°C for 3 hours. After cooling, 2 mL of 2.5% (w/v) NaCl was added, and fatty acyl
chains were extracted in 300 µL of hexane. Samples were analyzed by GC-FID and GC-MS as
previously described (Domergue et al., 2010).

For FAME analysis in yeast, wild-type *Saccharomyces cerevisiae* or INVSc1 strains transformed with
KCS4, *KCS9* or the empty vector (EV), were grown in 5 mL of appropriate liquid minimal medium for
1 week at 30°C, then pelleted and washed in 2 mL of 2.5% (w/v) NaCl. Yeast cell pellets were
resuspended in 1 mL 0.5 M sulfuric acid in methanol containing 2% (v/v) dimethoxypropane and 20
µg of heptadecanoic acid (C17:0) as internal standard and transmethylation was performed at 85°C
for 1 hour.

Confocal microscopy

Live imaging was performed using a Leica SP5 confocal laser scanning microscopy system (Leica,
Wetzlar, Germany) equipped with Argon, DPSS, He-Ne lasers, hybrid detectors and 63x oil-
immersion objective. Two days post agroinfiltration, *N. benthamiana* leaf samples were gently

transferred between a glass slide and a cover slip in a drop of water. The plasmid ER-gk CD3-955 was used as a fluorescent ER marker (Nelson et al., 2007). YFP and GFP fluorescence were observed using excitation wavelength of 488 nm and their fluorescence emission was collected at 490–540 nm.

Biomass determination

Plants (WT and KO lines) from Pr0 and Sh0 accessions were grown as described in experimental design for CHD and immediately weighed after harvested.

Geographic and phylogenetic signal of the lipidome

The neighbor-joining tree was constructed by BioNJ algorithm (Gascuel, 1997), using J-C distance in SeaView 4.4.3 software(Gouy et al., 2010). Phylogenetic signal was computed using K statistics and as a background a Brownian motion model of trait evolution (Blomberg et al., 2003) in the 'picante' R package (Kembel et al., 2010). Significance of the phylogenetic signal was estimated by comparison of observed variance patterns to a null model obtained by 9,999 random permutations of the accession labels across the phylogeny. The altitude at the sites was estimated using the geomapdata database (Lees, 2000) based on the latitude and longitude coordinates. The climate conditions have been downloaded from the WorldClim database (www.worldclim.org (Fick and Hijmans, 2017)). The lipidomic data were regressed against the geodesic distance matrix using non-parametric multivariate variance analysis (Anderson, 2001). The relationship between lipid levels and the climate parameters was analyzed using regularized regression model (Friedman et al., 2010). The regularization parameter alpha and penalty parameters lambda were estimated using 10-fold cross-validation within the training set. In result the Elastic Net regularization with parameter alpha = 0.5 was selected as optimal and applied for all regression models and the 'λmin + 1SE'-rule was applied to choose the penalty parameter for each model separately. Prediction power was estimated in Monte Carlo cross-validation test with 100 samples with 57% and 25% of samples taken as a training and test set respectively. Kruskal-Wallis and Wilcoxon rank sum tests have been performed using the R stats package.

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Author contribution

Acknowledgements

We would like to thank Prof. Dr. Lothar Willmitzer for discussion, support and the opportunity to
develop the project. In addition, we acknowledge Änne Michaelis, Gudrun Wolter and Simy Weil for
their outstanding technical assistance in LC-MS measurements, and Dr. Karin Kohl for her help in
plant cultivation. We thank Hezi Tenenboim for his editorial aid. CMF is a career member of the
National Research Council (CONICET). This research was supported by the Israel Science Foundation
(grant no. 859/19).

Competing interests

The authors declare no competing interests.

Figure legends

Figure 1. Results from GWAS analysis on lipidomic data from plants grown under control (CHD)
and stress (HD) conditions.

a. Chromosome scheme and Quantitative Trait Loci (QTL) identified in the two experimental
conditions (CHD = circles, HD = squares), for different lipid classes: phosphatidylethanolamine (PE),
phosphatidylcholine (lecithin) (PC), monogalactosyldiacylglycerol (MGDG), digalactosyldiacylglycerol
(DGDG), diacylglycerol (DAG) and triacylglycerol (TAG). Color/shape references are included in the
figure. Gene IDs are included only for co-localizing QTL for two or more lipid species with LOD > 5.3.

b. Manhattan plots obtained for TAG 54:9 in CHD (top) and in HD (bottom). The *KCS4* QTL was found
at Chromosome 1 only under HD condition. **c.** Pearson correlations coefficients calculated between
all lipid species across all accessions, for HD condition. Lipids are color-coded according to class and
clustered using Ward´s distance on pairwise dissimilarity. **d.** Average trait value (intensity of TAG
54:9, $\log_2$ scale) for the different *KCS4* haplotypes using SNPs m11502, m11503, m11504 and
m11505. **e.** TAG 54:9 average value for accessions carrying the KCS4(Met) and KCS4(Thr) alleles.

Figure 2. Dissection of *KCS4* alleles involved in TAG variation, pattern of linkage disequilibrium and
signatures of selection.

a. *KCS4* gene model depicting promoter region (P, green), 5'UTR (orange), coding region (yellow) and
3'UTR (orange) of AT1G19440/*KCS4*. Beginning, end and relevant SNP positions are indicated above
(TAIR10) and bellow (SNP ID) gene structure. **b.** Manhattan plot of GWAS results (HD: black circles;
3D: red circles) obtained for TAG 54:9 using re-sequenced information for 149 accessions. The re-
sequenced region on Chromosome 1 (positions 6689119 to 6769118, TAIR10) included 131 SNPs
genotyped in the 250K SNPchip plus 1,137 additional polymorphisms. Bonferroni threshold (LOD =
4.4) is indicated with a horizontal dashed line. **c**. Linkage disequilibrium (LD) is depicted as a heat
map of the coefficient of correlation (r^2). The LD block ($0.8 > r^2 > 0.2$, $P < 0.001$) includes the lead
SNPs rs21933 and m11481, SNPs in *KCS4* promoter (rs39451, rs39499, m11502), in *KCS4* genomic
region (m11503) and in *KCS4* 3'UTR (m11504). **d.** Tajima's D value in sliding windows for the genomic
region analyzed in **(b)**. Gene models and gene orientation are depicted with grey arrows, *KCS4* is
highlighted in yellow. Significantly negative Tajima's D values are marked with asterisks (*$P < 0.05$,
**$P < 0.01$).

Figure 3. *KCS4* functional validation using knock-out mutants in Arabidopsis and heterologous
expression in *Nicotiana benthamiana*.

a and b. Average TAG profiles for wild-type (WT) accessions and knock-out (KO) mutants carrying the
KCS4(Met) allele (WT: red; KO: pink) and the *KCS4*(Thr) allele (WT: blue; KO: light-blue). TAG class 54
(from 54:1 to 54:9) is plotted for CHD and HD for two independent experiments. TAG class 56 was
only detected in the second experiment for 56:4, 56:5 and 56:6. One-way ANOVA followed by
Tuckey post-hoc test was performed to detect differences between lines. Significant changes (* $P <$
0.05) were detected between accessions with different genetic background (red and pink vs. blue
and light-blue). No significant differences were found for the KO lines compared with their WT
counterparts. **c.** Transient expression of At*KCS4* in *Nicotiana benthamiana* leaves. TAG levels for
classes 52 (52:0 - 52:8), 54 (54:0 - 54:9) and 56 (56:0 - 56:0) for the control line and for the At*KCS4*
line (At*KCS4*, black circles). Significant values (*t*-Test) are indicated (° $P < 0.1$, * $P < 0.01$, ** $P <$
0.001).

Figure 4. KCS4 transcriptional regulation.

a. Percentage of transcription factors (TF) classes predicted to bind *KCS4* genomic region according
to *in-silico* analysis of binding motives using DAP-seq database(O'Malley et al., 2016). **b.** Position of
the binding motifs (red rectangles) for the main TF classes. SNP positions in the promoter and in
coding region are marked with horizontal dash-lines and names are stated above gene model. **c.**
Electrophoretic Mobility Shift Assay (EMSA) showing the interaction between *HEAT SCHOCK FACTOR*
A2 (*HSFA2*/AT2G26150) and the HSE binding motif (heat shock element: 5'- nnGnAnnTnCtn -3')
found within the SNP m11502 in *KCS4* promoter region; 1: labelled probe (5'-DY682-labelled
double-stranded oligonucleotide) only; 2: labelled probe plus HSFA2-GST protein; 3: labelled probe,
HSFA2-GST protein and 200× competitor DNA (unlabeled oligonucleotide containing HSE binding site
with the "C" allele at m11502), 4: well spill, 5: labelled probe plus free GST, 6: labelled probe,

HSFA2-GST protein and 200× competitor DNA (unlabeled oligonucleotide containing HSE binding site
with the "T" allele at m11502). **d.** *KCS4* expression for the complete GWAS population in CHD and HD
conditions, grouped based on C or T allele at SNP m11502 in *KCS4* promoter region. Expression (fold
change) was measured by qRT-PCR. Significant differences between CHD and HD transcript levels
and between C and T alleles are shown (*t*-Test: * $P < 0.05$, ** $P < 0.001$, *** $P < 0.0001$, n.s. not
significant). Data represent means ± SD (three technical replicates per sample). **e.** Average trait value
(TAG 54:9 intensity, in $\log_2$) for the two major haplotypes determined by SNPs m11502 (promoter)
and m11503 (coding region). CT and TC haplotypes encodes for *KCS4*(Met) and *KCS4*(Thr),
respectively. Significant differences between haplotypes (*t*-Test: * $P < 0.05$). **f.** Heatmap of
expression pattern for 16 members of the *KCS* multigene family clustered using complete-average
method. Transcript abundance was measured 24 hours after treatment. Data was obtained
previously(Caldana et al., 2011).

Figure 5. KCS4 activity and specificity in fatty-acid elongation and subcellular localization.

a. Very long chain fatty acid methyl ester (VLC-FAME) profiles (16 to 18 and 20 to 26, separate
panels) of wild-type yeast transformed with an empty vector (orange) and *AtKCS4* (blue). **b.** VLC-
FAME profiles (16 to 18 and 20 to 26, separate panels) of Δelo3 yeast mutant transformed with an
empty vector (grey), *AtKCS4* (blue bars) and *AtKCS9* (green). **c.** VLC-FAME profiles (20 to 30) from
leaves of *Nicotiana benthamiana* control plants (pink) or transformed with *AtKCS4* (blue). Significant
differences are shown (*t*-Test: * $P < 0.05$, ** $P < 0.001$, *** $P < 0.0001$). **d.** Confocal images of *N.
benthamiana* leaves transiently transformed with KCS4-YFP construct. The plasmid ER-GK CD3-955
was used as an ER marker. Bars = 20 µm.

Figure 6. Biomass changes in *kcs4* mutants.

936   Wild-type Arabidopsis accessions and knock-out mutants for Pro-0 and Sh-0, carrying *KCS4*(Met) or
937   *KCS4*(Thr), respectively. *t*-Test for rosette fresh weight (g) (* $P < 0.05$, *** $P < 0.001$).

Figure 7. *KCS4* haplotype correlation with climate and geographic parameters.

a. Heatmap of the mean values of lipid, climate and geographical variables for each of the four KCS4
haplotypes (SNPs m11502-m11503). Results of the *KCS4* locus association as well as nonparametric
ANOVA test (Kruskal-Wallis) are highlighted in the row-annotation bar. Cluster dominated by KCS4-
associated TAGs is highlighted in red. **b.** Average haplotype value for: the principal component 1
(PC1) obtained using the data in KCS4 cluster (red triangle in **a**), and the climate and geographical
parameter showing significant Kruskal-Wallis in **a**. Significant differences are shown (pairwise
Wilcoxon rank sum test: * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$).

Figure 8. Model summarizing the role of KCS4 on FA fate in Arabidopsis under carbon starvation.

The lack of *de novo* FA synthesis under HD induces the degradation of galactolipids (MGDGs and
DGDGs) from the chloroplasts' thylakoids by lipases (HIL1). FFAs are then exported to the ER (FA-CoA
pool), where KCS4 is localized and acts as a branch point in the fate of FAs, directing the saturated
ones to the very-long-chain fatty-acid pathway (VLCFA). Two *KCS4* alleles have differential capacity
to allocate saturated FAs into the VLCFA pathway, with a major -more efficient- allele, *KCS4*(Met),
and a minor -weaker- allele, *KCS4*(Thr), exemplified here as red and blue, respectively.
Polyunsaturated TAG (pu TAGs) levels are, therefore, higher in *KCS4*(Met) accessions comparing to
KCS4(Thr) accessions, as the result of a rise in the ratio of polyunsaturated-to-saturated FAs (pu/sa
FA-CoA). The activation of DEWAX transcription factors under darkness inhibits wax biosynthesis.
Therefore, VLCFA-CoA produced by the elongase complex (here exemplified by KCS4, KCR, HCD, ECR)
could directly serve as a source of carbon, and undergo degradation in the peroxisome. pu TAGs are

accumulated in lipid bodies. FFAs are released from lipid bodies by the action of lipases (SDP1/LIP1)
and further imported to the peroxisome to undergo β-oxidation. ACXs are key enzymes for FA
degradation and they have been also implicated in the IBA to IAA conversion in the peroxisome.
ACX3 and *ACX6* have been detected as putative regulators of KCS4. Acronyms: ABCA9 (ATP-BINDING
CASSETTE A9), ACBP-1 (Acyl-CoA-binding protein 1); ACX (ACYL-COA OXIDASE); CoA (Coenzyme A);
DGDG (Digalactosyldiacylglycerol); *DEWAX* (*DECREASE WAX BIOSYNTHESIS*), ECR (ENOYL-COA
REDUCTASE); FAs (fatty acids); FAS (fatty-acid synthesis); FAX1 (FATTY ACID EXPORT1); FFAs (free
fatty acids); HCD (β-HYDROXYACYL-COA DEHYDRATASE); HIL1 (HEAT INDUCIBLE LIPASE1); IAA (indol-
3-acetic-acid), IBA (indol-3-butyric-acid), KCR (β-KETOACYL REDUCTASE); KCS4(Met/Thr) (3-
KETOACYL-COA SYNTHASE 4); LACS (LONG-CHAIN ACYL-COA SYNTHETASE); SDP1/LIP1 (LIPASE 1);
MGDG (Monogalactosyldiacylglycerol); PXA1 (PEROXISOMAL ABC-TRANSPORTER 1); pu
(polyunsaturated), sa (saturated), TAGs (Triacylglycerols); VLCFA (Very-long-chain-fatty-acid).

Supplementary Figure 1. Phenotypic analyses for the Arabidopsis GWAS panel under control and
stress conditions

a. Principal component analysis (PCA) of lipid data for control condition (CHD, blue circles) and heat
and dark condition (HD, red diamonds). Each dot represents a single accession. PC1 and PC2 explain
together 67.5% of the variance observed in the phenotypic data. **b.** Heatmap of differential
accumulation of lipid levels in stress (HD) and control (CHD) conditions. Lipids are clustered by lipid
class. For each accession, the lipid level in HD was subtracted by the lipid level in CHD. Positive
values (red) denote higher levels of lipid in HD condition, negative values (blue) denote higher level
of lipid in CHD condition (scale= log2 (Δ of lipid intensity). **c**. Correlation pattern among lipid levels in
both conditions: CHD (blue rectangle) and HD (red rectangle). Pairwise Pearson correlations (r^2) were
calculated between each lipid across all accessions. Lipids are highlighted with colors according to
lipid classes (references included in the figure). **d.** Distribution of fold change of lipid–feature levels
across all accessions. For each lipid feature, fold change was calculated by dividing the average of
the five highest intensities measured in a given 5 accession by the average of the five lowest
intensities. Y-axes is expressed in percentage of (A) all metabolite features (N=109 in stress, N=98 in
CHD), (B) only TAG features (N=41 in stress, N= 30 in CHD) and (C) other lipid features (N=68 in stress
and N=68 in CHD).

Supplementary Figure 2. Results from GWAS analysis on lipidomic data from plants grown under
extended darkness (3D, 6D) conditions.

a. Chromosome scheme and Quantitative Trait Loci (QTL) identified in the two experimental
conditions (3D = circles, 6D = squares), for different lipid classes: phosphatidylethanolamine (PE),
phosphatidylcholine (lecithin) (PC), monogalactosyldiacylglycerol (MGDG), digalactosyldiacylglycerol
(DGDG), diacylglycerol (DAG) and triacylglycerol (TAG). Color/shape references are included in the
figure. Gene IDs are included only for QTL co-localizing for two or more lipid species with LOD score
> 5.3. **b.** Manhattan plots obtained for TAG 54:9 in 3D (left) and in 6D (right). **c.** Average trait value
(intensity of TAG 54:9, $\log_2$ scale) for the different *KCS4* haplotypes using SNPs m11502, m11503,
m11504 and m11505. **e.** TAG 54:9 average value for accessions carrying the KCS4(Met) and
KCS4(Thr) alleles.

Supplementary Figure 3. Phylogenetic signal of the lipidome

a. Distribution of the phylogenetic signal calculated for all measured lipids in HD and CHD conditions.
Only lipids exhibiting significant phylogenetic signal are labelled. Lipids significant in CHD and HD are
marked with blue and red dots, respectively. Compounds significant in both conditions (p<0.05) have

overlapping red and blue markers. **b.** K parameter distribution obtained for the TAG profiles in CHD
(control) and HD (treatment) condition according to(Blomberg et al., 2003).

Supplementary Figure 4. Prediction of climate parameters from lipidomic profiles

Regression coefficients of selected predictive lipidomic features towards 19 climate variables and 3
geographical coordinates (latitude, longitude and altitude) of the geographical origin of analyzed
accessions. Statistical evaluation of the fitted models is provided on the right-hand panel. The model
fit significance (red asterisks) is estimated by the correlation coefficient between the original and
model-fitted variable values. The significance of Cross-Validation test (black asterisks) represents the
significance of the correlation coefficient between the predicted and real values of the test sample.
The cross-validation has been performed 100 times with the 3:1 proportion of the training to test
sample set size.

Supplementary File 1.

Alignment used for the generation of the SNP matrix used in TASSEL to analyze more polymorphisms
in the QTL associated with *KCS4*. Sequences were obtained from the Arabidopsis 1001 genome
project (http://signal.salk.edu/atg1001/3.0/gebrowser.php, 162 accessions). TAIR10 positions of the
extract are chromosome 1: 6689119 - 6769118. Alignment was performed using MAFFT (Katoh et al.,
2019) and manually curated when needed.

Supplementary File 2.

Alignment of KCS4 sequences from wild type and knockout accessions used in this study.

Supplementary Table 1.

Phenotypic data used for GWAS and collected in: (1) control conditions for the heat and dark stress
treatment (CHD), (2) heat and dark stress (HD), (3) control conditions for the dark treatment (CD), (4)
three days extended darkness (3D) and (5) six days extended darkness. Each phenotype is in
different excel sheets. Plants were grown and harvested as described in Materials and Methods.
Lipid classes detected are DAG: dyacylglicerols, DGDG: digalactosyldiacylglycerol, MGDG:
monogalactosyldiacylglycerol, PC: phosphatidylcholine (lecithin), PE: phosphatidylethanolamine and
TAG: triacylglycerol. For each species the number of carbons and the degree of bond-saturation is
stated. Phenotypic value is the logarithm in the second base of intensity obtained in LC-MS.

Supplementary Table 2.

Table with GWAS results obtained from GAPIT for each phenotype presented in Supp. Table 1. All
SNPs with a LOD score > 5.3 for all traits obtained in the same condition are summarized in the same
table. Each sheet presents the results for each condition (see Supp. Table 1).
MAF:minorallelefrequency.

Supplementary Table 3.

Full list of GWAS results summarized in number of QTL (quatitative trait loci) and genes detected per
condition, for all lipid species phenotyped (LOD score >5.3). Co-localization between traits in the
same conditions are stated in "Peak.ID" columns. Co-localizing genes between CHD and HD
condition are also mentioned. Putative lipid functions for genes related to lipid biosynthesis
pathways are included in the last column. KCS4 association is highlighted in red. Each sheet compiles
results for all traits phenotyped in one condition (see Supp. Table 1)

Supplementary Table 4.

Data used for TASSEL analysis: Genotypic matrix, generated from the alignment in Supp. File 1;
principal components and kinship matrix used to control for population structure and confounding
effects. Phenotypic matrixes for HD and 3D are included in Supplementary Table 1.

Supplementary Table 5.

1047 GWAS results for HD and 3D data (see Supp. Table 1 for phenotype matrix and Supp. Table 4 for
1048 genotype matrix) using complete sequence information for 80 kb around KCS4. SNPs super-passing
1049 Bonferroni-corrected p-values (LOD > 4.38) are marked in bold. Markers ID in Tassel are referenced
1050 to positions in Supp. File 1, marker ID in GAPIT and TAIR10 position.

Supplementary Table 6.

1052 TAGs associated with *KCS4*, measured in Arabidopsis *kcs4* lines. Accession ID (common name), Type
1053 (wild type or mutant), KCS4_allele (Methionine or Threonine), Condition (control or HD) and number
1054 of experiment (Exp) are included in different columns. The table presents trait values for each
1055 biological replicate for accessions separately. Values in Figure 3 were obtained by averaging
1056 accessions encoding for a Methionine or Threonine, respectively for each type (WT and KO).

Supplementary Table 7.

1058 GWAS result summarized in number of eQTL (expression QTL) and genes detected using KCS4
1059 expression data in CHD and HD (LOD score of association > 5.0). Putative lipid functions for genes
1060 related to lipid biosynthesis pathways are included in the last column. Each sheet compiles results
1061 for all traits phenotyped in one condition (see Supp. Table 7)**.**

Supplementary Table 8.

1063 Primers and oligonucleotide sequences used in this study.

1064

Figure 1. Results from GWAS analysis on lipidomic data from plants grown under control (CHD) and stress (HD) conditions.

a. Chromosome scheme and Quantitative Trait Loci (QTL) identified in the two experimental conditions (CHD = circles, HD = squares), for different lipid classes: phosphatidylethanolamine (PE), phosphatidylcholine (lecithin) (PC), monogalactosyldiacylglycerol (MGDG), digalactosyldiacylglycerol (DGDG), diacylglycerol (DAG) and triacylglycerol (TAG). Color/shape references are included in the figure. Gene IDs are included only for co-localizing QTL for two or more lipid species with LOD > 5.3. **b.** Manhattan plots obtained for TAG 54:9 in CHD (top) and in HD (bottom). The *KCS4* QTL was found at Chromosome 1 only under HD condition. **c.** Pearson correlations coefficients calculated between all lipid species across all accessions, for HD condition. Lipids are color-coded according to class and clustered using Ward´s distance on pairwise dissimilarity. **d.** Average trait value (intensity of TAG 54:9, log₂ scale) for the different *KCS4* haplotypes using SNPs m11502, m11503, m11504 and m11505. **e.** TAG 54:9 average value for accessions carrying the *KCS4*(Met) and *KCS4*(Thr) alleles.

Figure 2. Dissection of *KCS4* alleles involved in TAG variation, pattern of linkage disequilibrium and signatures of selection.

a. *KCS4* gene model depicting promoter region (P, green), 5'UTR (orange), coding region (yellow) and 3'UTR (orange) of AT1G19440/*KCS4*. Beginning, end and relevant SNP positions are indicated above (TAIR10) and bellow (SNP ID) gene structure. **b.** Manhattan plot of GWAS results (HD: black circles; 3D: red circles) obtained for TAG 54:9 using re-sequenced information for 149 accessions. The re-sequenced region on Chromosome 1 (positions 6689119 to 6769118, TAIR10) included 131 SNPs genotyped in the 250K SNPchip plus 1,137 additional polymorphisms. Bonferroni threshold (LOD = 4.4) is indicated with a horizontal dashed line. **c.** Linkage disequilibrium (LD) is depicted as a heat map of the coefficient of correlation (r²). The LD block (0.8 > r² > 0.2, P < 0.001) includes the lead SNPs rs21933 and m11481, SNPs in *KCS4* promoter (rs39451, rs39499, m11502), in *KCS4* genomic region (m11503) and in *KCS4* 3'UTR (m11504). **d.** Tajima's D value in sliding windows for the genomic region analyzed in (**b**). Gene models and gene orientation are depicted with grey arrows, *KCS4* is highlighted in yellow. Significantly negative Tajima's D values are marked with asterisks (*P < 0.05, **P < 0.01).

Figure 3. *KCS4* functional validation using knock-out mutants in Arabidopsis and heterologous expression in *Nicotiana benthamiana*.

a and **b.** Average TAG profiles for wild-type (WT) accessions and knock-out (KO) mutants carrying the *KCS4*(Met) allele (WT: red; KO: pink) and the *KCS4*(Thr) allele (WT: blue; KO: light-blue). TAG class 54 (from 54:1 to 54:9) is plotted for CHD and HD for two independent experiments. TAG class 56 was only detected in the second experiment for 56:4, 56:5 and 56:6. One-way ANOVA followed by Tuckey post-hoc test was performed to detect differences between lines. Significant changes (* P < 0.05) were detected between accessions with different genetic background (red and pink vs. blue and light-blue). No significant differences were found for the KO lines compared with their WT counterparts. **c.** Transient expression of *AtKCS4* in Nicotiana benthamiana leaves. TAG levels for classes 52 (52:0 - 52:8), 54 (54:0 - 54:9) and 56 (56:0 - 56:0) for the control line and for the AtKCS4 line (*AtKCS4*, black circles). Significant values (*t*-Test) are indicated (° P < 0.1, * P < 0.01, ** P < 0.001).

Figure 4. *KCS4* transcriptional regulation.
a. Percentage of transcription factors (TF) classes predicted to bind *KCS4* genomic region according to in-silico analysis of binding motives using DAP-seq database (O'Malley et al., 2016). **b.** Position of the binding motifs (red rectangles) for the main TF classes. SNP positions in the promoter and in coding region are marked with horizontal dash-lines and names are stated above gene model. **c.** Electrophoretic Mobility Shift Assay (EMSA) showing the interaction between HEAT SCHOCK FACTOR A2 (AT2G26150/*HSFA2*) and the HSE binding motif (heat shock element: 5' nnGnAnnTnCtn -3') found within the SNP m11502 in KCS4 promoter region; 1: labelled probe (5'-DY682-labelled double-stranded oligonucleotide) only; 2: labelled probe plus HSFA2-GST protein; 3: labelled probe, HSFA2-GST protein and 200× competitor DNA (unlabeled oligonucleotide containing HSE binding site with the "C" allele at m11502), 4: well spill, 5: labelled probe plus free GST, 6: labelled probe, HSFA2-GST protein and 200× competitor DNA (unlabeled oligonucleotide containing HSE binding site with the "T" allele at m11502). **d.** *KCS4* expression for the complete GWAS population in CHD and HD conditions, grouped based on C or T allele at SNP m11502 in *KCS4* promoter region. Expression (fold change) was measured by qRT-PCR. Significant differences between CHD and HD transcript levels and between C and T alleles are shown (*t*-Test: * P < 0.05, ** P < 0.001, *** P < 0.0001, n.s. not significant). Data represent means ± SD (three technical replicates per sample). **e.** Average trait value (TAG 54:9 intensity, in log2) for the two major haplotypes determined by SNPs m11502 (promoter) and m11503 (coding region). CT and TC haplotypes encodes for *KCS4*(Met) and *KCS4*(Thr), respectively. Significant differences between haplotypes (*t*-Test: * P < 0.05). **f.** Heatmap of expression pattern for 16 members of the KCS multigene family clustered using complete-average method. Transcript abundance was measured 24 hours after treatment. Data was obtained previously (Caldana et al., 2011).

Figure 5. *KCS4* activity and specificity in fatty-acid elongation and subcellular localization.
a. Very long chain fatty acid methyl ester (VLC-FAME) profiles (16 to 18 and 20 to 26, separate panels) of wild-type yeast transformed with an empty vector (orange) and *AtKCS4* (blue). **b.** VLC-FAME profiles (16 to 18 and 20 to 26, separate panels) of elo3 yeast mutant transformed with an empty vector (grey), *AtKCS4* (blue bars) and *AtKCS9* (green). **c.** VLC-FAME profiles (20 to 30) from leaves of *Nicotiana benthamiana* control plants (pink) or transformed with *AtKCS4* (blue). Significant differences are shown (*t*-Test: * P < 0.05, ** P < 0.001, *** P < 0.0001). **d.** Confocal images of *N. benthamiana* leaves transiently transformed with KCS4-YFP construct. The plasmid ER-GK CD3-955 was used as an ER marker. Bars = 20 μm.

Figure 6. Biomass changes in *kcs4* mutants.

Wild-type Arabidopsis accessions and knock-out mutants for Pro-0 and Sh-0, carrying *KCS4*(Met) or *KCS4*(Thr), respectively. *t*-Test for rosette fresh weight (g) (* P < 0.05, *** P < 0.001).

Figure 7. *KCS4* haplotype correlation with climate and geographic parameters.
a. Heatmap of the mean values of lipid, climate and geographical variables for each of the four *KCS4* haplotypes (SNPs m11502-m11503). Results of the **KCS4** locus association as well as nonparametric ANOVA test (Kruskal-Wallis) are highlighted in the row-annotation bar. Cluster dominated by *KCS4*-associated TAGs is highlighted in red. **b.** Average haplotype value for: the principal component 1 (PC1) obtained using the data in KCS4 cluster (red triangle in **a**), and the climate and geographical parameter showing significant Kruskal-Wallis in **a**. Significant differences are shown (pairwise Wilcoxon rank sum test: * P < 0.05, ** P < 0.01, *** P < 0.001).

Figure 8. Model summarizing the role of KCS4 on FA fate in Arabidopsis under carbon starvation.
The lack of de novo FA synthesis under HD induces the degradation of galactolipids (MGDGs and DGDGs) from the chloroplasts' thylakoids by lipases (HIL1). FFAs are then exported to the ER (FA-CoA pool), where KCS4 is localized and acts as a branch point in the fate of FAs, directing the saturated ones to the very-long-chain fatty-acid pathway (VLCFA). Two KCS4 alleles have differential capacity to allocate saturated FAs into the VLCFA pathway, with a major -more efficient- allele, *KCS4*(Met), and a minor -weaker- allele, *KCS4*(Thr), exemplified here as red and blue, respectively. Polyunsaturated TAG (pu TAGs) levels are, therefore, higher in *KCS4*(Met) accessions comparing to *KCS4*(Thr) accessions, as the result of a rise in the ratio of polyunsaturated-to-saturated FAs (pu/sa FA-CoA). The activation of *DEWAX* transcription factors under darkness inhibits wax biosynthesis. Therefore, VLCFA-CoA produced by the elongase complex (here exemplified by KCS4, KCR, HCD, ECR) could directly serve as a source of carbon, and undergo degradation in the peroxisome. pu TAGs are accumulated in lipid bodies. FFAs are released from lipid bodies by the action of lipases (SDP1/LIP1) and further imported to the peroxisome to undergo β-oxidation. ACXs are key enzymes for FA degradation and they have been also implicated in the IBA to IAA conversion in the peroxisome. *ACX3* and *ACX6* have been detected as putative regulators of KCS4. Acronyms: ABCA9 (ATP-BINDING CASSETTE A9), ACBP-1 (Acyl-CoA-binding protein 1); ACX (ACYL-COA OXIDASE); CoA (Coenzyme A); DGDG (Digalactosyldiacylglycerol); *DEWAX* (*DECREASE WAX BIOSYNTHESIS*), ECR (ENOYL-COA REDUCTASE); FAs (fatty acids); FAS (fatty-acid synthesis); FAX1 (FATTY ACID EXPORT1); FFAs (free fatty acids); HCD (β-HYDROXYACYL-COA DEHYDRATASE); HIL1 (HEAT INDUCIBLE LIPASE1); IAA (indol-3-acetic-acid), IBA (indol-3-butyric-acid), KCR (β-KETOACYL REDUCTASE); KCS4(Met/Thr) (3-KETOACYL-COA SYNTHASE4); LACS (LONG-CHAIN ACYL-COA SYNTHETASE); SDP1/LIP1 (LIPASE 1); MGDG (Monogalactosyldiacylglycerol); PXA1 (PEROXISOMAL ABC-TRANSPORTER 1); pu (polyunsaturated), sa (saturated), TAGs (Triacylglycerols); VLCFA (Very-long-chain-fatty-acid).

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Author contribution

YB and CMF conceived the project and supervised the study. UL conducted GWAS experiments, obtained and selected KO mutants, performed experimental validation with KO, statistical analysis and interpretation of results. A-KR help UL in experimental work and performed analysis of the phenotypic data. JJ and MB conducted experiments on tobacco and yeast lines. JSz conducted the phylogenetic and geographical-signal analysis. VPTK provided expertise and assistance on TF analysis and advised on EMSA experiment and qRT-PCR assay. ML and SW assist in GWAS and multivariate analysis. FZ provided the plant material and carried out the lipid profiling for 3D and 6D GWAS. NE and SK helped UL in qRT-PCR assay for GWAS population and KO validation. JSc obtained KO constructs for transformation of Arabidopsis. AS provided access to LC-MS. ARF and AS help with discussion. CMF performed TASSEL, LD, Tajima´s D and haplotype analyses, analysed and interpreted the results and helped with data visualization. CMF and UL wrote the paper with input from YB, JJ, JSz and YL-B. All authors read and draft the manuscript.

Acknowledgements

We would like to thank Prof. Dr. Lothar Willmitzer for discussion, support and the opportunity to develop the project. In addition, we acknowledge Änne Michaelis, Gudrun Wolter and Simy Weil for their outstanding technical assistance in LC-MS measurements, and Dr. Karin Kohl for her help in plant cultivation. We thank Hezi Tenenboim for his editorial aid. CMF is a career member of the National Research Council (CONICET). This research was supported by the Israel Science Foundation (grant no. 859/19).

Competing interests

The authors declare no competing interests.