Hello darkness, my old friend: 3-Ketoacyl-Coenzyme A Synthase4 is a branch point in the regulation of triacylglycerol synthesis in *Arabidopsis thaliana*

Urszula Luzarowska[1], Anne-Kathrin Ruß[2], Jérôme Joubès[3], Marguerite Batsale[3], Jędrzej Szymański[4], Venkatesh Periyakavanam Thirumalaikumar[2], Marcin Luzarowski[2], Si Wu[5], Feng Zhu[2,6], Niklas Endres[2], Sarah Khedhayir[2], Julia Schumacher[7], Weronika Jasinska[1], Ke Xu[2], Sandra Marcela Correa Cordoba[1], Simy Weil[1], Aleksandra Skirycz[2], Alisdair Robert Fernie[2], Yonghua Li-Beisson[8], Corina Mariana Fusari[9*†], Yariv Brotman[1*†]

[1] Department of Life Sciences, Ben Gurion University of the Negev, Beersheva, Israel

[2] Max Planck Institute of Molecular Plant Physiology, Am Mühlenberg 1, 14476 Potsdam-Golm, Germany

[3] University Bordeaux, CNRS, Laboratoire de Biogenèse Membranaire, UMR 5200, F-33140 Villenave d'Ornon, France.

[4] Department of Molecular Genetics, Leibniz Institute of Plant Genetics and Crop Plant Research, OT Gatersleben, 06466, Seeland, Germany

[5] Department of Genetics, Stanford University School of Medicine, Stanford, CA 94305, USA

[6] National R&D Center for Citrus Preservation; Key Laboratory of Horticultural Plant Biology, Ministry of Education; Huazhong Agricultural University, Wuhan 430070, P.R. China

[7] Department for Plant Cell and Molecular Biology, Institute for Biology, Humboldt-Universität zu Berlin, Philippstraße 13, 10115 Berlin, Germany

[8] Aix Marseille Univ., CEA, CNRS, BIAM, Institute de Biosciences et Biotechnologies Aix-Marseille, F-13108 Saint Paul-Lez-Durance, France

[9] Centro de Estudios Fotosintéticos y Bioquímicos (CEFOBI-CONICET-UNR), Suipacha 570, S2000LRJ Rosario, Argentina

[†] Senior Authors

*Corresponding authors:
Yariv Brotman: brotmany@post.bgu.ac.il; Corina M. Fusari: fusari@cefobi-conicet.gov.ar

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 under carbon starvation, by acting as a regulatory branch point in the fate of fatty acids.

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 in very long chain fatty-acid (VLCFA) synthesis, underlies a differential accumulation of polyunsaturated triacylglycerols (puTAGs) 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. Allelic mutants and transient overexpression *in planta* revealed the differential role of *KCS4* alleles in VLCFA synthesis and wax coverage, puTAG accumulation and biomass. Moreover, the region harboring *KCS4* is under high selective pressure and 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 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. These 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).

Like many other complex traits, plant metabolism has an extended variation within natural populations, and therefore has been widely investigated by using genome-wide association studies (GWAS). Genetic factors involved in variation for key metabolic traits have been successfully identified and characterized (i.e., primary and secondary metabolites and enzyme activities) (Wu et al., 2016, 2018; Fusari et al., 2017). A number of GWAS regarding lipid metabolism have been reported and resulted in the identification of new enzymes and regulators in species like Arabidopsis, maize, coffee, rice and canola (Riedelsheimer et al., 2013; Gacek et al., 2017; Sant'Ana et al., 2018; Li et al., 2019; Hong et al., 2022). 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; Caldana et al., 2011; Szymanski et al., 2014). 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, the major source of energy in the dark is starch, which 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 due to limited starch availability. Under these conditions, polyunsaturated fatty acids (PUFA) released from membrane lipids are used as an alternative substrate for respiration via β-oxidation. These released fatty acids are often sequestered into triacylglycerols (TAGs) to avoid the adverse effects of the detergent-like properties of free fatty acids (FFAs). Therefore, it follows that TAG synthesis and lipid-droplet formation sometimes

constitute a cellular response to lipotoxicity. This sequestration is especially true for PUFA species
because they contain multiple double bonds and are liable to production of reactive oxygen species
(ROS) (Kao et al., 2018). 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). This work suggests that only by causing a
perturbation of the metabolic homeostasis is 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 four different environments: control,
combined heat and darkness, and two different extended darkness conditions. The locus harboring
KCS4, encoding for a *3-KETOACYL-COENZYME A SYNTHASE* (Joubès et al., 2008; Kim et al., 2021), was
strongly associated with a high number of polyunsaturated TAGs (puTAGs) in stress conditions, but
was not detected in control condition. Thus, *KCS4* association is driven by carbon starvation. Using
mutants for alternative *KCS4* alleles and ectopic expression in yeast and plants we explored the
biochemical properties of *KCS4* and validated its role in lipid metabolism. We place a model for *KCS4*
enzymatic and regulatory function, where *KCS4* acts as a branch point in the fate of FAs, directing
saturated FA to the very-long chain fatty acid pathway (VLCFA) and facilitating the pool of
polyunsaturated FA in the accumulation of puTAGs. Two *KCS4* alleles have differential capacity to
process saturated FA. Accessions carrying the strong allele show higher levels of VLCFA-derived
cuticular waxes and higher levels of puTAGs. 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 response to changing environments.

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 Dataset 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 genotypic information from 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). 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 Dataset 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 Dataset 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 Dataset 3,
Acyl-Lipid Metabolism database (Li-Beisson et al., 2010) http://aralip.plantbiology.msu.edu/) (Figure
1). After filtering for robust associations co-localizing for two or more traits, four QTL harbored lipid-
genes (Figure 1a). Two QTL in Chromosome 1, one harboring the *3-KETOACYL-COENZYME A*
SYNTHASE4 (*KCS4*, AT1G19440) and other including a *LIPASE CLASS 3* (AT1G06250), two *ACYL-COA*
OXIDASES (*ACX3*: AT1G06290 and *ACX6*: AT1G06310) and two *FATTY ACID DESATURASE* (*CER17*:
AT1G06350, ADS4.2: AT1G063609); one in Chromosome 3 harboring the *FATTY ACID DESATURASE*
(*FAD2*: AT3G12120) and the last QTL in Chromosome 5, harboring a *LYSOPHOSPHOLIPASE*
(AT5G20060) (Supplementary Dataset 3, Figure 1a).

3-KETOACYL-COENZYME A SYNTHASE4 is involved in fatty acid elongation and has major impact on
polyunsaturated TAG levels under heat and dark stress

Remarkably, 22 polyunsaturated TAGs (puTAGs) co-localized to the QTL on chromosome 1,
harboring *KCS4* (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-value < 0.05) for 16 of the 22
associated TAGs (e.g., TAG 54:9, Figure 1b; Supplementary Dataset 2). Besides *KCS4*, 33 other genes
mapped on the QTL, spanning 107,318 bp (Supplementary Dataset 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 (Rossak et al., 2001). However, KCS4
specificity and function have not been clearly characterized so far. TAGs associated with the *KCS4*
QTL were exclusively polyunsaturated (e.g., puTAG 52:6, 52:7, 54:6, 54:8, 54:9, 56:6, Supplementary.
Table 2-3) and correlated positively with each other, grouping together in a single well-defined
cluster (Figure 1c).

To identify the alleles involved in puTAG variation under HD, we constructed haplotypes considering
the four SNPs from *KCS4* scored in the 250K SNPchip (m11502, m11503, m11504, m11505,
Supplementary Dataset 2). The population divided into nine non-unique haplotypes, which were
therefore, further considered as being putatively involved in the QTL variation. Mean levels of
puTAG 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 puTAG 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 (m11503) in *KCS4* is the causal mutation
underlying puTAG variation under HD conditions in Arabidopsis.

KCS4 associates with polyunsaturated TAGs in extended darkness

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

For this purpose, we utilized own data sets: control (CD), 3 days (3D) extended darkness, and 6 days
(6D) extended darkness (Supplementary Dataset 1) (Zhu et al., 2022). 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 Dataset 2, Supplementary Dataset 3).
The locus harboring *KCS4* associated strongly in 3D and 6D with 8 and 13 puTAGs, respectively. Lead
SNP and other features of the association matched with GWAS results from the HD experiment
(Supplementary Figure 2). Thus, darkness alone is enough to trigger the association of *KCS4* with
puTAGs and could be related to the carbon status of the plant. Expression of *DIN1* (AT4G35770) and
BCAT2 (AT1G10070), two genes usually used as starvation markers (Moraes et al., 2019) are
upregulated under HD conditions (Supplementary Figure 3), showing that HD is also triggering
carbon starvation. In summary, an additive effect is observed when both stresses are applied
together, determining a stronger association of *KCS4* to puTAGs under HD.

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 Dataset 4) to perform GWAS with more SNPs than those included in the previous
experiments using the 250K 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 more 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 identified 35 additional SNPs in *KCS4*
genomic region apart from the 4 SNPs scored in the 250K SNPchip (19 in the promoter, two in the
5′UTR, 13 in the coding region, and one in the 3′UTR; Supplementary Dataset 5). Fewer TAGs with
lower LOD values showed association with *KCS4* gene region, as expected when analyzing a reduced
number of accessions (< 100) (Supplementary Dataset 5, Figure 2b). 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). Surprisingly, several SNPs in the *KCS4* coding
region did not associate (Figure 2b).

All SNPs in the locus harboring KCS4 with high LOD values 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 with the lead SNPs nor 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 and supports the selection of *KCS4* as the candidate gene involved in puTAG variation.

Transcriptional regulation of *KCS4* in Arabidopsis

Several SNPs in the promoter region showed significant LD with the non-synonymous SNP m11503.
Therefore, we deepened on the transcriptional regulation of *KCS4* in Arabidopsis (Figure 3). 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). Several transcription factor (TF) families
belonging to land plants could likely bind to the *KCS4* promoter region, indicating that *KCS4*
expression is controlled under several regulatory processes (Figure 3a). 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 colocalizing with
polymorphisms, but in other regions of the promoter (Figure 3b). 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.

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 3c, 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 3c, 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 3c, 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 3c, lane 6), suggesting that the T allele at
m11502 determines a stronger binding of HSF2A to the *KCS4* promoter region. Overall, this indicates
that polymorphisms at the promoter region could exert a dosage effect of transcription factors,
influencing the expression of *KCS4*.

Furthermore, we analyzed natural variation in transcript levels of *KCS4* for the CHD and HD
conditions in the complete GWAS panel (Figure 3d). *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 3e, TAG 54:9). In HD, *KCS4* transcript levels are
not significantly different for accessions carrying different alleles at m11502. This confirms that
neither differences in TF binding-affinity nor expression levels of *KCS4* determine variation of puTAG
levels under HD (Figure 3e). In other words, polymorphisms at *KCS4* promoter region are not the
causal for puTAG variation in Arabidopsis natural population.

Expression patterns of KCS family members under diverse environmental conditions

We analyzed the time-resolved response of Arabidopsis Col-0 accession towards light and
temperature for 16 of the 21 gene members using data previously obtained (Caldana et al., 2011).
Focusing on 24 h, 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 transcript levels are much lower in HD, strengthening 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 to *KCS4* across several environmental stimuli
(Figure 3f).

KCS4 functional validation in puTAG variation

To validate the role of *KCS4* alleles in puTAG variation under HD stress, we selected five accessions:
three carrying *KCS4*(Met) and two carrying *KCS4*(Thr). Selection of these accessions was based on
puTAG levels measured in the HD experiment (Supplementary Dataset 1). Mutant lines (*kcs4*) 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 as
described in materials and methods and harvested to perform lipidomic analysis. Since natural
variation is detected at a population level, we compared average values for *kcs4*(Met) and *kcs4*(Thr)
allelic mutants against wild-type *KCS4*(Met) and *KCS4*(Thr) alleles (Figure 4).

Under control conditions (CHD), puTAG levels (X:4 to X:9) are significantly different between
KCS4(Met) and *kcs4*(Met) lines. Mutants for *kcs4*(Met) presented, in average, lower levels of
puTAGs, similar to the levels found for *KCS4*(Thr) accessions (Figure 4 a-c, j-k). This phenomenon is
seen for the accessions pooled together as well as for individual accessions (data not shown). On the
other hand, puTAG levels did not differ between *KCS4*(Thr) and *kcs4*(Thr). These results support
KCS4(Met) as the stronger allele and the causal polymorphism for polyunsaturated TAG variation.

Under HD condition, a higher accumulation of puTAGs is seen for accessions carrying *KCS4*(Met)
allele (Figure 4 d-f, j-k). However, overall levels of TAGs (saturated and polyunsaturated) increase
independently of *KCS4* alleles. This is in agreement with the phenotype observed for the complete
mapping panel. Here, mutants don't differ in puTAG levels from their wild-type counterparts, as if
the massive production of puTAGs under stress overrides the solely effect of *KCS4* mutation.

Transient expression of At*KCS4*(Met) in *N. benthamiana* leaves showed significantly higher levels of
puTAGs for classes 52, 54, and 56 compared to control plants (Figure 4 g-i). Conversely, TAGs with
none 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*.

In summary, the reduction of puTAGs in the *kcs4*(Met) mutant (Figure 4 a-c, j-k), together with the
increasement of puTAGs when *KCS4*(Met) in ectopically expressed in *N. benthamiana* (Figure 4 g-i),
confirms that *KCS4*(Met) is the causal polymorphism for polyunsaturated TAG variation and validate
GWAS results.

KCS4 functional validation in the accumulation of cuticular waxes

VLCFAs are produced by the elongation complex (i.e., KCS, KCR: β-KETOACYL REDUCTASE, HCD: β-
HYDROXYACYL-COA DEHYDRATASE and ECR: ENOYL-COA REDUCTASE) in the Endoplasmic Reticulum
(ER) and used as precursors for the synthesis of lipid barriers such as cuticular waxes. Therefore, we
determined the wax coverage for *KCS4* wild-type alleles and mutants as a proxy of the enzyme
activity *in planta* (Figure 4 l-m). Under CHD, lines carrying *KCS4*(Met) showed higher content of
waxes than lines carrying <u>*KCS4*</u>(Thr). The mutant *kcs4*(Met) showed a significant reduction of the
major components of leaf waxes: C29 and C31 *n*-alkanes, C26 and C28 *n*-alcohols, C30 and C32
aldehydes, C28 and C30 fatty acids. On the contrary, *kcs4*(Thr) does not show differences to its wild-
type counterpart. Under HD, the total wax content is increased in the different lines and significant
differences are seen between Met and Thr alleles but not between wild type and mutants. These

results confirm that the wax coverage and composition is different for both alleles, and that other
members of the KCS family cannot fully complement the synthesis of waxes coming from FA
elongated by KCS4.

KCS4 enzymatic activity and cellular localization

KCS4 shows sequence 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 they determine the substrate specificity.

To evaluate the very-long-chain 3-ketoacyl-CoA synthase activity and substrate specificity of KCS4,
we expressed *AtKCS4*(Met) in wild-type yeast and profiled VLCFAs (Figure 5). The strain expressing
AtKCS4(Met) synthesized significantly higher levels of VLCFA from C20 to C26 compared to the strain
transformed with an empty vector (Figure 5a).

We further expressed *AtKCS4*(Met) in the Δ*elo3* yeast strain, lacking the endogenous ELO3 elongase
(Figure 5b). The Δ*elo3* strain accumulates C20 and C22 VLCFA (Han et al., 2002). Expression of KCS4
led to the elongation of VLCFAs from C22 to C24 and from C24 to C26 (Figure 5b). We also analyzed
heterologous expression of At*KCS9* as it is the closest *KCS4* homolog (Figure 5b). KCS9 elongates
VLCFAs from C22 to C24 (Kim et al., 2013 and Figure 5b). 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*(Met) in *N. benthamiana* leaves showed a significant decrease of C20
and C22 VLCFAs and a significant increase of VLCFAs from C26 up to C30 compared to the control
(Figure 5c). The elongation of VLCFAs up to C30 might be the result of the action of the native
elongase complex in *N. benthamiana* due to increased availability of C26 when *KCS4* is transiently
expressed. AtKCS4(Met)-YFP was found to label a polygonal and tubular network characteristic of
the ER (Figure 5d), in agreement with previous results shown for other KCS family members(Joubès
et al., 2008).

We further transformed Δ*elo3* strain with *KCS4* wild-type and mutant alleles (Supplementary Figure
4). Expression of both *KCS4*(Met) and *KCS4*(Thr) alleles led to the elongation of C22 into C24 up to
C26 VLCFA in the Δ*elo3* strain with slight differences in the amount of C22 and 2OH-C24
(Supplementary Figure 4a). On the other hand, yeast expressing allelic mutants do not show exactly
the composition of the control line, C26 is not accumulated but C22 and C24 VLCFA are still
produced at low level compared to yeast expressing wild-type alleles, as if some activity remains.
This residual accumulation of VLCFA in the mutants indicates that *kcs4*(Met) and *kcs4*(Thr) lines still
have some enzymatic activity, although very weak.

In addition, we performed a time-point experiment at 48, 72 and 96 h for Δ*elo3* strain expressing
KCS4(Met) *and KCS4*(Thr) wild-type alleles (Supplementary Figure 4b). We could detect that, yeasts
expressing *KCS4*(Met) ended up with more C26 and 2OH:C26 than yeasts expressing *KCS4*(Thr),
supporting the hypothesis of a differential enzymatic activity between *KCS4* alleles.

KCS1 expression in yeast leads to the production of C18, C20 and C22 VLCFA (Trenkamp et al., 2004;
Tresch et al., 2012), KCS2 can elongate from C20 to C22 (Millar et al., 1999; Franke et al., 2009),
KCS20 mainly produces C22 and C24 VLCFA, KCS5 and KCS6 mainly produce C24 to C28. All these
proteins have different expression profiles under heat and dark stress, some of them upregulated
and some of them downregulated (Figure 3f). Expression profiles of KCS4, KCS5, KCS9 and KCS12 are
also altered in *kcs4* CRISPR-Cas lines, evidencing a delicate expression balance under stress, between
KCS family proteins (Supplementary Figure 5).

Biomass is affected by KCS4 function

It has been demonstrated that a mild reduction in VLCFA content improve cell proliferation and
shoot growth (Nobusawa et al., 2013). To investigate if *KCS4* exert an effect in plant growth, we
compared biomass for *KCS4* wild-type accessions and mutant lines. We collected full rosettes from
plants grown in CHD and subjected to HD, immediately after treatment. The *kcs4* mutants grew
significantly bigger than their WT counterparts (Figure 6). This indicates that biomass is negatively
correlated with KCS4 activity and further supports both the idea that mutations at *KCS4* reduce the
overall content of VLCFA and that KCS4 activity cannot be overcome by other family members.

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 6).

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 7). 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 (Figure
7). Eight climate parameters plus latitude and longitude differed significantly between haplotypes ($p
< 0.05$, Figure 7a). Moreover, five of them co-clustered with TAGs associated with *KCS4*, four of them
related to precipitation and one to temperature (isothermality). The "TT" haplotype in most cases,
presented the lowest value for these parameters, suggesting that the allelic effect of these two SNPs
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
control conditions and subjected to a sudden environmental change, given by a combined stress of
heat and darkness. 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 what
was found for glycerolipids in rice (Hong et al., 2022) and for primary metabolites in maize and
Arabidopsis (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
(Chan et al., 2011; Matsuda et al., 2012; Wen et al., 2014; Wu et al., 2018).

In our study, applying combined heat and darkness resulted in a strong perturbation of lipid
homeostasis. This led to the identification of a large-effect QTL at Chromosome 1, harboring *KCS4*.
KCS4 associated with several polyunsaturated TAGs (puTAGs) specifically under carbon starvation
conditions (HD, 3D and 6D) in a highly robust manner (Figure 1b, Supplementary Figure 2b,
Supplementary Dataset 2/3). Under HD, all puTAGs mapping to *KCS4* are higher than under CHD, but
accessions carrying *KCS4*(Met) always have higher levels of puTAGs than accessions carrying
KCS4(Thr). PuTAGs that mapped to *KCS4* clustered together and correlated negatively to saturated
TAGs, further illustrating the role of *KCS4* in the specific regulation of puTAGs (Figure 1c).

We have provided several lines of proof that both *KCS4* is the causal gene for TAG variation and
KCS4(Met) allele determines higher levels of puTAGs under stresses (HD, 3D, 6D): (i) linkage
disequilibrium, correlation among lipid species and haplotypic analysis point *KCS4* as the candidate
gene for puTAG variation under stress (Figure 1, Figure 2), (ii) transient overexpression of *KCS4*(Met)
in *N. benthamiana* mimics the phenotype we observed in the GWAS population grown under stress
conditions (Figure 4 g-i), (iii) lipidomic analysis of allelic mutants (*kcs4*(Met)/*kcs4*(Thr)) and their
respective wild-type accessions (*KCS4*(Met)/*KCS4*(Thr)) shows a clear phenotype on puTAG, VLCFA
and wax components (Figure 4, Figure 5, Supplementary Figure 5).

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). This result is in
agreement with Kim et al. (2021) findings for *kcs4* TDNA mutant, which accumulates C22 and C24.
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
showed 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 4
d-f, g-i). In addition, TAG levels are significantly different when comparing *KCS4*(Met) with its allelic
mutant *kcs4*(Met) in control conditions (CHD) (Figure 4 a-k). In the same line of evidence, the mutant
kcs4(Met) showed a significant reduction of the major components of leaf waxes compare to its
wild-type allele in CHD (Figure 4 l-m). Not unexpectedly, *kcs4*(Thr) did not show any differences in
TAG levels of wax compounds compared to *KCS4*(Thr). It has been previously shown in GWAS, that
mutating the weaker allele did not always result in clear phenotypic changes for the traits under
study (Todesco et al., 2010; Fusari et al., 2017; Wang et al., 2022; Yang et al., 2022).

The phenotype can also 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). Under HD, there is
a strong metabolomic and expression reprogramming as shown before for lipids and primary and
secondary metabolites (Burgos et al., 2011; Szymanski et al., 2014; Wu et al., 2016, 2018). This could
explain why we cannot observe a phenotype by mutating only one gene. 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 (Joubès et al., 2008; Guo et

al., 2016) and we have shown that expression of other KCS members is altered in *kcs4* allelic
mutants, indicating a complex regulation between *KCS* genes (Supplementary Figure 5). Of note, the
nature of this complex regulation was recently demonstrated to involve protein-protein interactions
within the elongase complex (Kim et al., 2022).

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.

In an event of sudden extended darkness (3D, 6D) or combined heat and darkness (HD), plants
become carbon starved (Supplementary Figure 3) (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). There are many lines of evidence that support the idea that plant lipids
are alternative sources of carbon and energy under stress, particularly under carbon starvation. For
instance, Kunz et al. (2009) showed that by knocking out the PXA1 transporter, the import of FFA
into the perixosome is blocked, resulting in plants dying faster in extended darkness. Fan et al.
(2017), through the study of SDP1/LIP1 mutants, could define the crucial role that TAG metabolism
has in membrane lipid breakdown, fatty acid turnover, and plant survival under extended darkness.
Other study showed that there are different metabolic strategies employed by leaves in response to
different darkening treatments (Law et al., 2018). These strategies involve either importing sugars
from sink sources, metabolizing amino acids or activating the turnover of lipids from the plastid
membranes to the b-oxidation in the peroxisome. The last strategy is particularly important after 6
days of dark treatment. Finally, Yu et al. (2018) demonstrated that the disruption of starch synthesis
resulted in a significant increase in FA synthesis via post-translational regulation of the plastidial
acetyl-coenzyme A carboxylase and a concurrent increase in the synthesis and turnover of
membrane lipids and triacylglycerol.

To summarize our findings, we present a model of lipid remodeling under heat and dark stress in
Arabidopsis (Figure 8). In the proposed model, darkness induces the predominant response within
the combined stress, blocking *de novo* FA synthesis (*de novo* 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 (Higashi et al., 2015; Fan et al., 2017). 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). *KCS4*(Met) accessions are, as well, efficiently channeling the
saturated FA from the Acyl-CoA pool to cuticular waxes, as they present higher accumulation of
waxes than *KCS4*(Thr) accessions under stress (Figure 4). 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 (Figure 4). 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).

Our work demonstrates that KCS4 is a key enzyme involved in the regulation of puTAG levels under heat and darkness and under extended darkness alone, adding complexity to lipid-metabolism regulation under carbon starvation. The enzymatic function of KCS4 in the synthesis of VLCFA is affecting the accumulation of the unsaturated Acyl-CoA pool (16:3 and 18:3, for example) and the sequestration of them into puTAGs.

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 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 (100 mg for each sample) 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) (Alseekh et al., 2021).

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 Dataset 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 Dataset 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 Dataset 4). Lipid features collected formerly (HD and 3D)
Supplementary Dataset 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 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 Dataset 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 Dataset 7. 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 Dataset 7. 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 *Δelo3* [MATa *his3Δ1 leu2 trp1-289 ura3-52 elo3Δ*] were used to express *KCS4* wild-type and
allelic mutants and *KCS9*.

623 qRT-PCR and eQTL analysis

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).
GAPDH3 (AT1G13440) was used as reference gene for starvation markers and *KCS* transcripts
analysis. All primers used are listed in Supplementary Dataset 7.

qRT-PCR was performed on three biological replicates per ecotype. 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 *GAPDH3* 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.

639 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
Dataset 7. 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.

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

For fatty acid methyl esters (FAMEs) analysis 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. For FAMEs analysis in yeast, yeasts 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. 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).

661 Cuticular wax analysis

Epicuticular waxes were extracted from leaves by immersing tissues for 30 s in chloroform
containing docosane (C22 alkane) as internal standard. Extracts were derivatized and analyzed as
previously described (Bourdenx et al., 2011).

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 were grown and treated as described for lipid measurements. Plants from wild-type
accessions carrying *KCS4*(Met) and *KCS4*(Thr) as well as allelic mutants *kcs4*(Met) and *kcs4*(Thr) were
grown in CHD or treated for 24 h with HD and harvested right after (CHD and HD at the same time).
Biomass measurement was performed on complete rosettes (n=3 ± SD) for each line. Results from
accessions or mutants were then pooled according to the allele carried.

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.

References

Alseekh, S. et al. (2021). Mass spectrometry-based metabolomics: a guide for annotation,
quantification and best reporting practices. Nature Methods 2021 18:7 18: 747–756.

Anderson, M.J. (2001). A new method for non-parametric multivariate analysis of variance.
Austral Ecol 26: 32–46.

Baxter, I., Brazelton, J.N., Yu, D., Huang, Y.S., Lahner, B., Yakubova, E., Li, Y., Bergelson, J.,
Borevitz, J.O., Nordborg, M., Vitek, O., and Salt, D.E. (2010). A coastal cline in sodium

accumulation in Arabidopsis thaliana is driven by natural variation of the sodium
transporter AtHKT1;1. PLoS Genet 6: e1001193.

Blacklock, B.J. and Jaworski, J.G. (2006). Substrate specificity of Arabidopsis 3-ketoacyl-CoA
synthases. Biochem Biophys Res Commun 346: 583–590.

Blomberg, S.P., Garland Jr, T., and Ives, A.R. (2003). Testing for phylogenetic signal in
comparative data: behavioral traits are more labile. Evolution (N Y) 57: 717–745.

Bourdenx, B., Bernard, A., Domergue, F., Pascal, S., Léger, A., Roby, D., Pervent, M., Vile, D.,
Haslam, R.P., Napier, J.A., Lessire, R., and Joubès, J. (2011). Overexpression of Arabidopsis
ECERIFERUM1 promotes wax very-long-chain alkane biosynthesis and influences plant
response to biotic and abiotic stresses. Plant Physiol 156: 29–45.

Bradbury, P.J., Zhang, Z., Kroon, D.E., Casstevens, T.M., Ramdoss, Y., and Buckler, E.S. (2007).
TASSEL: software for association mapping of complex traits in diverse samples.
Bioinformatics 23: 2633–5.

Burgos, A., Szymanski, J., Seiwert, B., Degenkolbe, T., Hannah, M.A., Giavalisco, P., and
Willmitzer, L. (2011). Analysis of short-term changes in the Arabidopsis thaliana
glycerolipidome in response to temperature and light. The Plant Journal 66: 656–668.

Caldana, C., Degenkolbe, T., Cuadros-Inostroza, A., Klie, S., Sulpice, R., Leisse, A., Steinhauser,
D., Fernie, A.R., Willmitzer, L., and Hannah, M.A. (2011). High-density kinetic analysis of
the metabolomic and transcriptomic response of Arabidopsis to eight environmental
conditions. The Plant Journal 67: 869–884.

Chan, E.K.F., Rowe, H.C., Corwin, J.A., Joseph, B., and Kliebenstein, D.J. (2011). Combining
genome-wide association mapping and transcriptional networks to identify novel genes
controlling glucosinolates in Arabidopsis thaliana. PLoS Biol 9.

Correa, S.M., Fernie, A.R., Nikoloski, Z., and Brotman, Y. (2020). Towards model-driven
characterization and manipulation of plant lipid metabolism. Prog Lipid Res: 101051.

Czechowski, T., Stitt, M., Altmann, T., Udvardi, M.K., and Scheible, W.R. (2005). Genome-wide
identification and testing of superior reference genes for transcript normalization in
arabidopsis. Plant Physiol.

Dittrich-Domergue, F., Joubès, J., Moreau, P., Lessire, R., Stymne, S., and Domergue, F. (2014).
The bifunctional protein TtFARAT from Tetrahymena thermophila catalyzes the formation
of both precursors required to initiate ether lipid biosynthesis. Journal of Biological
Chemistry 289: 21984–21994.

Domergue, F., Vishwanath, S.J., Joubès, J., Ono, J., Lee, J.A., Bourdon, M., Alhattab, R., Lowe, C.,
Pascal, S., and Lessire, R. (2010). Three Arabidopsis fatty acyl-coenzyme A reductases,
FAR1, FAR4, and FAR5, generate primary fatty alcohols associated with suberin
deposition. Plant Physiol 153: 1539–1554.

Fan, J., Yan, C., Roston, R., Shanklin, J., and Xu, C. (2014). Arabidopsis lipins, PDAT1
acyltransferase, and SDP1 triacylglycerol lipase synergistically direct fatty acids toward β-
oxidation, thereby maintaining membrane lipid homeostasis. Plant Cell 26: 4119–4134.

Fan, J., Yu, L., and Xu, C. (2017). A Central Role for Triacylglycerol in Membrane Lipid
Breakdown, Fatty Acid β-Oxidation, and Plant Survival under Extended Darkness. Plant
Physiol 174: 1517.

Fick, S.E. and Hijmans, R.J. (2017). WorldClim 2: new 1-km spatial resolution climate surfaces
for global land areas. International journal of climatology 37: 4302–4315.

Fraire-Velázquez, S. and Balderas-Hernández, V.E. (2013). Abiotic Stress in Plants and Metabolic
Responses. In Abiotic Stress - Plant Responses and Applications in Agriculture, K. Vahdati,
ed (Intech open), p. 25.

Franke, R., Höfer, R., Briesen, I., Emsermann, M., Efremova, N., Yephremov, A., and Schreiber,
L. (2009). The DAISY gene from Arabidopsis encodes a fatty acid elongase condensing
enzyme involved in the biosynthesis of aliphatic suberin in roots and the
chalaza-micropyle region of seeds. The Plant Journal 57: 80–95.

Friedman, J., Hastie, T., and Tibshirani, R. (2010). Regularization paths for generalized linear
models via coordinate descent. J Stat Softw 33: 1.

Fusari, C.M., Kooke, R., Lauxmann, M.A., Annunziata, M.G., Enke, B., Hoehne, M., Krohn, N.,
Becker, F.F.M.M., Schlereth, A., Sulpice, R., Stitt, M., and Keurentjes, J.J.B. (2017).
Genome-wide association mapping reveals that specific and pleiotropic regulatory
mechanisms fine-tune central metabolism and growth in Arabidopsis. Plant Cell 29: 2349–
2373.

Gacek, K., Bayer, P.E., Bartkowiak-Broda, I., Szala, L., Bocianowski, J., Edwards, D., and Batley, J.
(2017). Genome-wide association study of genetic control of seed fatty acid biosynthesis
in Brassica napus. Front Plant Sci 7: 1–13.

Gao, X. and Starmer, J. (2007). Human population structure detection via multilocus genotype
clustering. BMC Genet 8: 34.

Gascuel, O. (1997). BIONJ: an improved version of the NJ algorithm based on a simple model of
sequence data. Mol Biol Evol 14: 685–695.

Gouy, M., Guindon, S., and Gascuel, O. (2010). SeaView version 4: a multiplatform graphical
user interface for sequence alignment and phylogenetic tree building. Mol Biol Evol 27:
221–224.

Graf, A. and Smith, A.M. (2011). Starch and the clock: The dark side of plant productivity.
Trends Plant Sci 16: 169–175.

Guo, H.S., Zhang, Y.M., Sun, X.Q., Li, M.M., Hang, Y.Y., and Xue, J.Y. (2016). Evolution of the KCS
gene family in plants: The history of gene duplication, sub/neofunctionalization and
redundancy. Molecular Genetics and Genomics 291: 739–752.

Hall, T.A. (1999). BioEdit: a user-friendly biological sequence alignment editor and analysis
program for Windows 95/98/NT. In Nucleic acids symposium series (Information Retrieval
Ltd., c1979-c2000.: London), pp. 95–98.

Han, G., Gable, K., Kohlwein, S.D., Beaudoin, F., Napier, J.A., and Dunn, T.M. (2002). The
Saccharomyces cerevisiae YBR159w gene encodes the 3-ketoreductase of the microsomal
fatty acid elongase. Journal of Biological Chemistry.

Han, X. (2016). Lipidomics: Comprehensive Mass Spectrometry of Lipids D.M. Desiderio and J.A.
Loo, eds (Wiley).

Higashi, Y., Okazaki, Y., Myouga, F., Shinozaki, K., and Saito, K. (2015). Landscape of the
lipidome and transcriptome under heat stress in Arabidopsis thaliana. Sci Rep 5: 10533.

Hong, J. et al. (2022). Genetic architecture of seed glycerolipids in Asian cultivated rice. Plant
Cell Environ.

Horton, M.W. et al. (2012). Genome-wide patterns of genetic variation in worldwide
Arabidopsis thaliana accessions from the RegMap panel. Nat Genet 44: 212–6.

Hummel, J., Segu, S., Li, Y., Irgang, S., Jueppner, J., and Giavalisco, P. (2011). Ultra performance
liquid chromatography and high resolution mass spectrometry for the analysis of plant
lipids. Front Plant Sci 2: 54.

Joubès, J., Raffaele, S., Bourdenx, B., Garcia, C., Laroche-Traineau, J., Moreau, P., Domergue, F.,
and Lessire, R. (2008). The VLCFA elongase gene family in Arabidopsis thaliana:
Phylogenetic analysis, 3D modelling and expression profiling. Plant Mol Biol 67: 547–566.

Kao, Y.T., Gonzalez, K.L., and Bartel, B. (2018). Peroxisome function, biogenesis, and dynamics
in plants. Plant Physiol 176: 162–177.

Karimi, M., Inzé, D., and Depicker, A. (2002). GATEWAY[TM] vectors for Agrobacterium-mediated
plant transformation. Trends Plant Sci 7: 193–195.

Katoh, K., Rozewicki, J., and Yamada, K.D. (2019). MAFFT online service: multiple sequence
alignment, interactive sequence choice and visualization. Brief Bioinform 20: 1160–1166.

Kembel, S.W., Cowan, P.D., Helmus, M.R., Cornwell, W.K., Morlon, H., Ackerly, D.D., Blomberg,
S.P., and Webb, C.O. (2010). Picante: R tools for integrating phylogenies and ecology.
Bioinformatics 26: 1463–1464.

Kim, J., Jung, J.H., Lee, S.B., Go, Y.S., Kim, H.J., Cahoon, R., Markham, J.E., Cahoon, E.B., and
Suh, M.C. (2013). Arabidopsis 3-ketoacyl-coenzyme a synthase9 is involved in the
synthesis of tetracosanoic acids as precursors of cuticular waxes, suberins, sphingolipids,
and phospholipids. Plant Physiol 162: 567–580.

Kim, J., Kim, R.J., Lee, S.B., and Suh, M.C. (2022). Protein–protein interactions in fatty acid
elongase complexes are important for very-long-chain fatty acid synthesis. J Exp Bot 73:
3004–3017.

Kim, J., Lee, S.B., and Suh, M.C. (2021). Arabidopsis 3-Ketoacyl-CoA Synthase 4 is Essential for
Root and Pollen Tube Growth. Journal of Plant Biology 64: 155–165.

Kunz, H.H., Scharnewski, M., Feussner, K., Feussner, I., Flügge, U.I., Fulda, M., and Gierth, M.
(2009). The ABC Transporter PXA1 and Peroxisomal β-Oxidation Are Vital for Metabolism
in Mature Leaves of Arabidopsis during Extended Darkness. Plant Cell 21: 2733–2749.

Lämke, J., Brzezinka, K., Altmann, S., and Bäurle, I. (2016). A hit-and-run heat shock factor
governs sustained histone methylation and transcriptional stress memory. EMBO J 35:
162–175.

Law, S.R., Chrobok, D., Juvany, M., Delhomme, N., Lindén, P., Brouwer, B., Ahad, A., Moritz, T.,
Jansson, B.S., Gardeström, P., and Keech, O. (2018). Darkened Leaves Use Different
Metabolic Strategies for Senescence and Survival. Plant Physiol 177: 132–150.

Lees, J.M. (2000). Geotouch: Software for Three and Four Dimensional GIS in the Earth
Sciences. Comput Geosci 26: 751–761.

Li, H., Thrash, A., Tang, J.D., He, L., Yan, J., and Warburton, M.L. (2019). Leveraging GWAS data
to identify metabolic pathways and networks involved in maize lipid biosynthesis. Plant
Journal 98: 853–863.

Li-Beisson, Y. et al. (2010). Acyl-Lipid Metabolism. Arabidopsis Book 8: e0133.

Lipka, A.E. et al. (2012). GAPIT: genome association and prediction integrated tool.
Bioinformatics 28: 2397–2399.

Ludwig-Müller, J. (2011). Auxin conjugates: Their role for plant development and in the
evolution of land plants. J Exp Bot 62: 1757–1773.

Luo, J. (2015). Metabolite-based genome-wide association studies in plants. Curr Opin Plant
Biol 24: 31–38.

Matsuda, F., Okazaki, Y., Oikawa, A., Kusano, M., Nakabayashi, R., Kikuchi, J., Yonemaru, J.I.,
Ebana, K., Yano, M., and Saito, K. (2012). Dissection of genotype-phenotype associations
in rice grains using metabolome quantitative trait loci analysis. Plant Journal 70: 624–636.

Millar, A.A., Clemens, S., Zachgo, S., Michael Giblin, E., Taylor, D.C., and Kunst, L. (1999). CUT1,
an Arabidopsis Gene Required for Cuticular Wax Biosynthesis and Pollen Fertility, Encodes
a Very-Long-Chain Fatty Acid Condensing Enzyme. Plant Cell 11: 825–838.

Moraes, T.A., Mengin, V., Annunziata, M.G., Encke, B., Krohn, N., Höhne, M., and Stitt, M.
(2019). Response of the Circadian Clock and Diel Starch Turnover to One Day of Low Light
or Low CO2. Plant Physiol 179: 1457–1478.

Nelson, B.K., Cai, X., and Nebenführ, A. (2007). A multicolored set of in vivo organelle markers
for co-localization studies in Arabidopsis and other plants. The Plant Journal 51: 1126–
1136.

Nobusawa, T., Okushima, Y., Nagata, N., Kojima, M., Sakakibara, H., and Umeda, M. (2013).
Synthesis of very-long-chain fatty acids in the epidermis controls plant organ growth by
restricting cell proliferation. PLoS Biol 11.

O'Malley, R.C., Huang, S.C., Song, L., Lewsey, M.G., Bartlett, A., Nery, J.R., Galli, M., Gallavotti,
A., and Ecker, J.R. (2016). Cistrome and epicistrome features shape the regulatory DNA
landscape. Cell 165: 1280–1292.

Perraki, A., Cacas, J.-L., Crowet, J.-M., Lins, L., Castroviejo, M., German-Retana, S., Mongrand,
S., and Raffaele, S. (2012). Plasma membrane localization of Solanum tuberosum remorin
from group 1, homolog 3 is mediated by conformational changes in a novel C-terminal
anchor and required for the restriction of potato virus X movement. Plant Physiol 160:
624–637.

Pilkington, S.M., Encke, B., Krohn, N., Höhne, M., Stitt, M., and Pyl, E.T. (2015). Relationship
between starch degradation and carbon demand for maintenance and growth in

Arabidopsis thaliana in different irradiance and temperature regimes. Plant Cell Environ
38: 157–171.

Puranik, S., Kumar, K., Srivastava, P.S., and Prasad, M. (2011). Electrophoretic mobility shift
assay reveals a novel recognition sequence for Setaria italica NAC protein. Plant Signal
Behav 6: 1588–1590.

Qiu, X., Pang, Y., Yuan, Z., Xing, D., Xu, J., Dingkuhn, M., Li, Z., and Ye, G. (2015). Genome-wide
association study of grain appearance and milling quality in a worldwide collection of
indica rice germplasm. PLoS One 10: e0145577.

R Core Team (2019). R: A language and environment for statistical computing.

Raivo Kolde (2019). pheatmap: Pretty Heatmaps. R package version 1.0.12.

Riedelsheimer, C., Brotman, Y., Méret, M., Melchinger, A.E., and Willmitzer, L. (2013). The
maize leaf lipidome shows multilevel genetic control and high predictive value for
agronomic traits. Sci Rep 3.

Rossak, M., Smith, M., and Kunst, L. (2001). Expression of the FAE1 gene and FAE1 promoter
activity in developing seeds of Arabidopsis thaliana. Plant Mol Biol 46: 717–725.

Sant'Ana, G.C. et al. (2018). Genome-wide association study reveals candidate genes
influencing lipids and diterpenes contents in Coffea arabica L. Sci Rep 8: 1–12.

Schumacher, J., Kaufmann, K., and Yan, W. (2017). Multiplexed GuideRNA-expression to
Efficiently Mutagenize Multiple Loci in Arabidopsis by CRISPR-Cas9. Bio Protoc 7.

Shin, J.-H., Blay, S., McNeney, B., and Graham, J. (2006). LDheatmap: an R function for graphical
display of pairwise linkage disequilibria between single nucleotide polymorphisms. J Stat
Softw 16: 1–10.

Stacklies, W., Redestig, H., Scholz, M., Walther, D., and Selbig, J. (2007). pcaMethods-a
bioconductor package providing PCA methods for incomplete data. Bioinformatics 23:
1164–1167.

Stitt, M. and Zeeman, S.C. (2012). Starch turnover: pathways, regulation and role in growth.
Curr Opin Plant Biol 15: 282–292.

Szymanski, J., Brotman, Y., Willmitzer, L., and Cuadros-Inostroza, Á. (2014). Linking gene
expression and membrane lipid composition of Arabidopsis. Plant Cell 26: 915–928.

Tajima, F. (1989). Statistical method for testing the neutral mutation hypothesis by DNA
polymorphism. Genetics 123: 585–595.

Thirumalaikumar, V.P., Devkar, V., Mehterov, N., Ali, S., Ozgur, R., Turkan, I., Mueller-Roeber,
B., and Balazadeh, S. (2018). NAC transcription factor JUNGBRUNNEN 1 enhances drought
tolerance in tomato. Plant Biotechnol J 16: 354–366.

Todesco, M. et al. (2010). Natural allelic variation underlying a major fitness trade-off in
Arabidopsis thaliana. Nature 465: 632–636.

Tonsor, S.J., Alonso-Blanco, C., and Koornneef, M. (2005). Gene function beyond the single
trait: Natural variation, gene effects, and evolutionary ecology in Arabidopsis thaliana.
Plant Cell Environ.

Trenkamp, S., Martin, W., and Tietjen, K. (2004). Specific and differential inhibition of very-
long-chain fatty acid elongases from Arabidopsis thaliana by different herbicides.
Proceedings of the National Academy of Sciences 101: 11903–11908.

Tresch, S., Heilmann, M., Christiansen, N., Looser, R., and Grossmann, K. (2012). Inhibition of
saturated very-long-chain fatty acid biosynthesis by mefluidide and perfluidone, selective
inhibitors of 3-ketoacyl-CoA synthases. Phytochemistry 76: 162–171.

Wang, P., Guo, L., Morgan, J., Dudareva, N., and Chapple, C. (2022). Transcript and metabolite
network perturbations in lignin biosynthetic mutants of Arabidopsis. Plant Physiol.

Welti, R., Li, W., Li, M., Sang, Y., Biesiada, H., Zhou, H.E., Rajashekar, C.B., Williams, T.D., and
Wang, X. (2002). Profiling membrane lipids in plant stress responses: Role of
phospholipase Dα in freezing-induced lipid changes in arabidopsis. Journal of Biological
Chemistry 277: 31994–32002.

Wen, W. et al. (2015). Genetic determinants of the network of primary metabolism and their
relationships to plant performance in a maize recombinant inbred line population. Plant
Cell 27: 1839–1856.

Wen, W., Li, D., Li, X., Gao, Y., Li, W., Li, H., Liu, J., Liu, H., Chen, W., Luo, J., and Yan, J. (2014).
Metabolome-based genome-wide association study of maize kernel leads to novel
biochemical insights. Nat Commun 5.

Wu, S. et al. (2016). Combined use of genome-wide association data and correlation networks
unravels key regulators of primary metabolism in Arabidopsis thaliana. PLoS Genet 12: 1–
31.

Wu, S., Tohge, T., Cuadros-Inostroza, Á., Tong, H., Tenenboim, H., Kooke, R., Méret, M.,
Keurentjes, J.B., Nikoloski, Z., Fernie, A.R., Willmitzer, L., and Brotman, Y. (2018). Mapping
the Arabidopsis Metabolic Landscape by Untargeted Metabolomics at Different
Environmental Conditions. Mol Plant 11: 118–134.

Yang, L., Wang, Z., Zhang, A., Bhawal, R., Li, C., Zhang, S., Cheng, L., and Hua, J. (2022).
Reduction of the canonical function of a glycolytic enzyme enolase triggers immune
responses that further affect metabolism and growth in Arabidopsis. Plant Cell 34: 1745–
1767.

Yu, L., Fan, J., Yan, C., and Xu, C. (2018). Starch deficiency enhances lipid biosynthesis and
turnover in leaves. Plant Physiol 178: 118–129.

Zhu, F. et al. (2022). Genome-wide association of the metabolic shifts underpinning dark-
induced senescence in Arabidopsis. Plant Cell 34: 557–578.

Author Contribution

analysis. FZ provided the plant material and carried out the lipid profiling for 3D and 6D GWAS. NE,
SK and SM helped UL in qRT-PCR assay for GWAS population and KO validation. HX and WJ
performed lipid profiling for *kcs4* mutants. 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, UL and YB wrote the paper with input from, 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 and Gudrun Wolter 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) and leader of a Max Planck Partner Group. This research was supported
by the Israel Science Foundation (grant no. 859/19).

Competing interests

956   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 names 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 (see reference at right) and clustered using Ward's distance on pairwise dissimilarity. A zoom-in
of the TAG cluster shows the grouping pattern of TAGs according to number of unsaturated bonds
and to the GWAS result (left). **d.** Average trait value (intensity of TAG 54:9, log2 scale) for the
different *KCS4* haplotypes using SNPs m11502, m11503, m11504 and m11505. The two major
haplotypes have the alternative alleles for m11503 (Met or Thr) **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 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 4. *KCS4* functional validation using allelic mutants in Arabidopsis and heterologous
expression in *Nicotiana benthamiana*.

a-f and j-k. Average TAG profiles for wild-type (WT) accessions and allelic mutants carrying the
KCS4(Met) allele (WT: red; mutant: pink) and the *KCS4*(Thr) allele (WT: blue; mutant: light-blue) in
CHD and HD conditions. One-way ANOVA followed by Tukey post-hoc test was performed to detect
differences between lines. Significant changes (* $P < 0.05$) are marked with asterisks (**a-f**) and with
letters for 52 TAG series and 54 TAG series (**j-k**). **g-h-i.** 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 (grey circles) and for the At*KCS4* line (black circles). Significant values (*t*-Test) are
indicated (° $P < 0.1$, * $P < 0.01$, ** $P < 0.001$). **l-m.** Cuticular wax coverage for the same accessions
grown in CHD or HD conditions. One-way ANOVA followed by Tukey post-hoc test was performed to
detect differences between lines (* $P < 0.05$). n.s.: Not significantly different.

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 At*KCS4* (blue). **b.** VLC-
FAME profiles (16 to 18 and 20 to 26, separate panels) of Δelo3 yeast mutant transformed with an
empty vector (grey), At*KCS4* (blue bars) and At*KCS9* (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* wild-type and allelic mutants.

Rosettes fresh-weight measured in accessions carrying KCS4(Met) or KCS4(Thr), and their respctive
allelic mutants. Plants were grown in control conditions (CHD) or subjected to heat and darkness for
24 h (HD) and harvested after the treatment. Significant differences were obtained using *t*-Test (* P
< 0.05).

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.

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. 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, channeling saturated FAs to VLCFA
elongation and tipping the balance to a higher polyunsaturated-to-saturated-FA ratio for puTAG
accumulation (degrade grey arrows). 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 and in different sizes, respectively.
KCS4(Met) accessions efficiently channel the saturated FA from the Acyl-CoA pool to cuticular waxes,
as they present higher accumulation of waxes than *KCS4*(Thr) accessions under stress. In addition,
polyunsaturated TAG (puTAGs) 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 going to
TAG formation. VLCFA-CoA produced by the elongase complex (here exemplified by KCS4, KCR, HCD,
ECR) go to increase the cuticular waxes under HD, and/or directly serve as a source of carbon
undergoing degradation in the peroxisome; whereas puTAGs accumulated into lipid bodies first.
FFAs are then released from lipid bodies by the action of lipases (SDP1/LIP1) and further imported to
the peroxisome to undergo β-oxidation. Acronyms: ABCA9 (ATP-BINDING CASSETTE A9), ACBP-1
(Acyl-CoA-binding protein 1); ACX (ACYL-COA OXIDASE); CoA (Coenzyme A); DGDG
(Digalactosyldiacylglycerol); ECR (ENOYL-COA REDUCTASE); FAs (fatty acids); FAS (fatty-acid
synthesis); FAX1 (FATTY ACID EXPORT1); FFAs (free fatty acids); HCD (β-HYDROXYACYL-COA
DEHYDRATASE); 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).

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 accessions 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. Quantification of starvation markers in KCS4 wild-type accessions and allelic mutants.

Transcripts were measured in 5 accessions, 3 carrying *KCS4*(Met) and two carrying *KCS4*(Thr), and five allelic mutants from those 5 accessions. Plants were grown in control conditions (CHD) or subjected to heat and darkness for 24 h (HD) and harvested both group at the same time point. Three biological replicates were used for each line, results from separate accessions were pooled according to the allele carried. Fold change of expression was obtained using the $2^{-(\Delta\Delta CT)}$ method using GAPDH3 (At1g13440) as housekeeping gene. Statistical significance was performed with ANOVA followed by Fisher LSD. Means with a common letter are not significantly different (P > 0.05).

Supplementary Figure 4. KCS4 enzymatic activity

a. Very long chain fatty acid methyl ester (VLC-FAME) profiles (22 to 26) of Δelo3 yeast mutant transformed with wild-type At*KCS4*(Met)/At*KCS4*(Thr) and allelic mutans *kcs4*(Met)/*kcs4*(Thr). References for colors are in the figure. Significant differences between alleles obtained with *t*-Test: ° P < 0.1, ** P < 0.01, *** P < 0.001. **b.** VLC-FAME profiles (22 to 26) at different times of harves (48, 72 and 96 h) for At*KCS4*(Met) and At*KCS4*(Thr) wild-type alleles. Significant differences were obtained with ANOVA followed by Tukey test (P < 0.05).

Supplementary Figure 5. Quantification of *KCS4*, *KCS5*, *KCS9* and *KCS12* transcripts in wild-type
***KCS4*(Met)/*KCS4*(Thr) accessions and kcs4(Met)/kcs4(Thr) allelic mutants.**

Transcripts were measured in 5 accessions, 3 carrying *KCS4*(Met) and two carrying *KCS4*(Thr), and
five allelic mutants from those 5 accessions. Plants were grown in control conditions (CHD) or
subjected to heat and darkness for 24 h (HD) and harvested both group at the same time point.
Three biological replicates were used for each line, results from separate accessions were pooled
according to the allele carried. Fold change of expression was obtained using the $2^{-(\Delta\Delta CT)}$ method
using GAPDH3 (At1g13440) as housekeeping gene. Statistical significance was performed with
ANOVA followed by Fisher LSD. Means with a common letter are not significantly different (P > 0.05).

Supplementary Figure 6. 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 7. 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 Dataset 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 Dataset 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: minor allele
frequency.

Supplementary Dataset 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 Dataset 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 Dataset 1.

Supplementary Dataset 5.

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

Supplementary Dataset 6.

All lipids measured in Arabidopsis wild-type accessions and *kcs4* allelic mutants. Accession ID
(common name), Type (wild type or mutant), KCS4_allele (Methionine or Threonine), Condition
(control or HD) are included in different columns. The table presents trait values for each biological
replicate for accessions separately. Values in Figure 4 were obtained by averaging accessions
encoding for a Methionine or Threonine, respectively for each type (WT and KO).

Supplementary Dataset 7.

Primers and oligonucleotide sequences used in this study.

1186

Figure 1. Results from GWAS on lipidomic data from plants grown under control (CHD) and heat and darkness (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 names 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 (see reference at right) and clustered using Ward´s distance on pairwise dissimilarity. A zoom-in of the TAG cluster shows the grouping pattern of TAGs according to number of unsaturated bonds and to the GWAS result (left) **d.** Average trait value (intensity of TAG 54:9, $\log_2$ scale) for the different *KCS4* haplotypes using SNPs m11502, m11503, m11504 and m11505. The two major haplotypes have the alternative alleles for m11503 (Met or Thr) **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* 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 4

Figure 4. *KCS4* **functional validation using allelic mutants in Arabidopsis and heterologous expression in *Nicotiana benthamiana*.**

a-f. Average TAG profiles for wild-type (WT) accessions and allelic mutants carrying the *KCS4*(Met) allele (WT: red; mutant: pink) and the *KCS4*(Thr) allele (WT: blue; mutant: light-blue) in CHD and HD conditions. One-way ANOVA followed by Tukey post-hoc test was performed to detect differences between lines. Significant changes (* $P < 0.05$) are marked with asterisks **(a-f)** and in detail for 52 TAG series and 54 TAG series **(j-k)**. **g-h-i.** 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 (grey circles) and for the At*KCS4*(Met) line (black circles). Significant values (*t*-Test) are indicated (° $P < 0.1$, * $P < 0.01$, ** $P < 0.001$). **l-m.** Cuticular wax coverage for the same accessions grown in CHD or HD conditions. One-way ANOVA followed by Tukey post-hoc test was performed to detect differences between lines (* $P < 0.05$). n.s.: Not significantly different.

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 wild-type accessions and allelic mutants.

Rosettes fresh-weight measured in accessions carrying *KCS4*(Met) or *KCS4*(Thr), and their respctive allelic mutants. Plants were grown in control conditions (CHD) or subjected to heat and darkness for 24 h (HD) and harvested after the treatment. Significant differences were obtained using *t*-Test (* P < 0.05).

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. 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, channeling saturated FAs to VLCFA elongation and tipping the balance to a higher polyunsaturated-to-saturated-FA ratio for puTAG accumulation (degrade grey arrows). 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 and in different sizes, respectively. *KCS4*(Met) accessions efficiently channel the saturated FA from the Acyl-CoA pool to cuticular waxes, as they present higher accumulation of waxes than KCS4(Thr) accessions under stress. In addition, polyunsaturated TAG (puTAGs) 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 going to TAG formation. VLCFA-CoA produced by the elongase complex (here exemplified by KCS4, KCR, HCD, ECR) go to increase the cuticular waxes under HD, and/or directly serve as a source of carbon undergoing degradation in the peroxisome; whereas puTAGs accumulated into lipid bodies first. FFAs are then released from lipid bodies by the action of lipases (SDP1/LIP1) and further imported to the peroxisome to undergo β-oxidation. Acronyms: ABCA9 (ATP-BINDING CASSETTE A9), ACBP-1 (Acyl-CoA-binding protein 1); ACX (ACYL-COA OXIDASE); CoA (Coenzyme A); DGDG (Digalactosyldiacylglycerol); ECR (ENOYL-COA REDUCTASE); FAs (fatty acids); FAS (fatty-acid synthesis); FAX1 (FATTY ACID EXPORT1); FFAs (free fatty acids); HCD (β-HYDROXYACYL-COA DEHYDRATASE); 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).