Transcriptional Response of *Chlamydomonas* reinhardtii to Small Lipid-Inducing Molecules

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1 Introduction

2 Targeted gene expression analysis using quantitative PCR

3 Role of exogenous citrate in lipid production

4 Transcriptome analysis using next-generation RNA sequencing

5 Discussion

Introduction

Microalgae as a feedstock for biofuel production Methods in the

literature for lipid induction in microalgae

High-throughput screening for lipid-inducing small molecules

Next-generation sequencing and bioinformatics

Introduction

- 1.1 Microalgae as a feedstock for biofuel production
- 1.2 Methods in the literature for lipid induction in microalgae
- 1.3 High-throughput screening for lipid-inducing small molecules
- 1.4 Next-generation sequencing and bioinformatics

Introduction

microalgae

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Microalgae as a feedstock for biofuel production

- Global challenges of climate change and energy crisis
- Biodiesel: versatility and the high energy efficiency
- Microalgae: alternative feedstock for biodiesel production
- Commercial production of algal biodiesel requires higher lipid content

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Methods in the literature for lipid induction in microalgae

- Nutrient starvation stimulates accumulation of TAG
 - N starvation induces up to 15-fold increase in lipid bodies
 - sta6 mutant shows higher lipid accumulation during N starvation
- Often accompanied by rapid autophagic processes
 - protein recycling
 - degradation of chloroplast and ribosome
 - turnover of membrane lipids

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High-throughput screening for lipid-inducing small molecules

- High-throughput screening (HTS) to identify modifiers of molecular targets and cellular processes
- We identified small molecules that induce lipid accumulation with minimal impact on growth using model organism *Chlamydomonas reinhardtii*
- Four structurally diverse compounds were selected for this study

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Introducti

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| Table 1.1: Structural information of small molecules identified in HTS | | | |
|--|----------------------------|--|---------------------|
| ID^1 | ChemBridge ID ² | Structure | Lab ID ³ |
| | | 0 N*.0 | |
| 30 | 5345030 | | WD30030 |
| 42 | 5950542 | HCI | WD20542 |
| 67 | 5234067 | N. N | WD20067 |
| 84 | 6719794 | N N N N N N N N N N N N N N N N N N N | W/D1079 <i>4</i> |
| 04 | 6718784 | , or ~ | WD10784 |

³Designation used in our lab based on chemical scaffolds



¹ID of compound used in this study

²Unique identifier used by ChemBridge (supplier of compounds)

Introduction

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Next-generation sequencing and bioinformatics

Next-generation sequencing and bioinformatics

- Next-generation RNA sequencing (RNA-seq): accurate measurement of expression and disovery of novel transcription w/o the need of hybridization
- Big data need efficient and statistically sound algorithms
- We have employed peer-reviewed tools developed by the bioinformatics community
 - TopHat/Bowtie 2: fast short reads alignment to the genome
 - Cufflinks: transcript assembly based on graph algorithm
 - eXpress: fast abundance estimation with mapping ambiguity resolution
 - GSEA: statistical information on the level of biological process

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Targeted gene

expression
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Analysis of
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 - 2.2 Analysis of differential gene expression

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analysis using quantitative PCI Growth and lipid accumulation Analysis of differential gene

expression

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rargeted gene expression analysis using quantitative PCF

Growth and lipid accumulation Analysis of differential gene expression

Growth and lipid accumulation

- Cells treated with compounds at a concentration of 20 μM each
- Except for compound 84, the impact on growth and photosynthesis not as severe as nitrogen starvation
- Up to 6-fold increase in lipid bodies in cells treated with compound 84
- 3- to 5-fold increase in lipid bodies in cells treated with compound 30 or 42

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expression
analysis using
quantitative PCF

Growth and lipid accumulation Analysis of differential gene expression

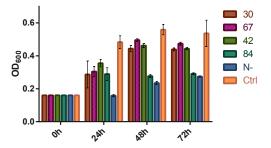


Figure 2.1: Growth under compound treatment. Cell density at 0h, 24h, 48h and 72h was estimated by optical density at 600 nm for each treatment and control. Three biological replicates were used for each condition.

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expression
analysis using
quantitative PC

Growth and lipid accumulation Analysis of differential gene expression

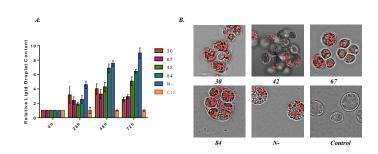


Figure 2.2: Lipid droplet accumulation during compound treatment. **A.** Lipid droplet content at 0h, 24h, 48h and 72h was estimated by fluorescence intensity after cells were stained with Nile red for each treatment and control. The fold change of fluorescence intensity relative to control was normalized by cell density in OD_{600} . Three biological replicates were used for each condition. **B.** Representative confocal microscopic images of cells stained with Nile red after 72h of incubation

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expression
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Analysis of
differential gene

expression

Analysis of differential gene expression

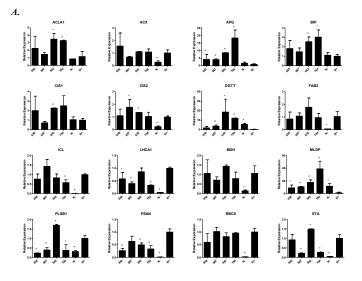
- Increased expression in DGTT and MLDP, involved in TAG biosynthesis
- Increased expression in ACL and CIS1, involved in citrate efflux from mitochondria
- Expression genes involved in photosynthesis NOT severely suppressed
- Increase expression in APG8 and BIP, involved in stress response

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Targeted gene expression analysis using quantitative PCF Growth and lipid accumulation

Analysis of differential gene expression



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Targeted gene expression analysis using quantitative PC Growth and lipid accumulation Analysis of differential gene expression

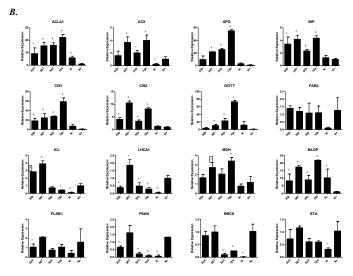


Figure 2.3: Expression of selected genes under different treatments. *: p < 0.05 and ^: p < 0.01. **A.** 24h of incubation. **B.** 72h of incubation.

Role of exogenous citrate in lipid production

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- 3.1 Introduction

Role of exogenous citrate in lipid production

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Introduction

- Genes involved in citrate efflux from mitochondria were significantly up-regulated
- ATP-citrate lyase catalyzes the conversion of citrate to acetyl-CoA
- Cytosolic acetyl-CoA can be used in fatty acid biosynthesis, leading to TAG accumulation

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citrate in lipid production

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Growth and lipid accumulation

- Enhanced cell growth with citrate supplementation
- Up to 5-fold increase in lipid bodies with 5 mM citrate
- FAMEs assay showed 1.5-fold increase in total FA and distinct FA composition

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Role of exogenous citrate in lipid production

Growth and lipid accumulation Uptake of citrate from the media

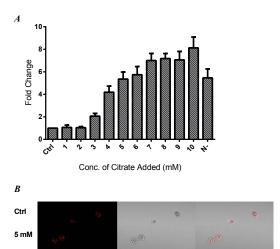


Figure 3.1: Lipid droplets accumulation during citrate supplementation. A. Normalized Nile red fluorescence. B. Confocal image at 72h of incubation.

8 mM N-

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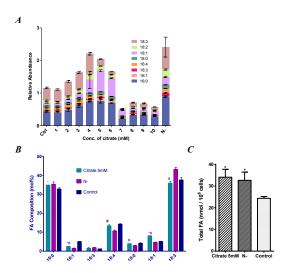


Figure 3.2: FAMEs profiles during citrate supplementation. **A.** Relative abundance of FA species at different citrate concentration. **B.** FA composition after 72h of incubation. **C.** Total FA after 72h of incubation, normalized to cell count.

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citrate in lipid production Introduction Growth and lipid accumulation

Uptake of citrate from the media

Uptake of citrate from the media

- GC/MS was used to determine the amount of citrate in the cells and media
- 30-fold increase of citrate in the cells after 24h treatment with 5 mM citrate
- Citrate concentration in the media decreased over time

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citrate in lipid
production

Growth and lipid accumulation

Uptake of citrate from the media

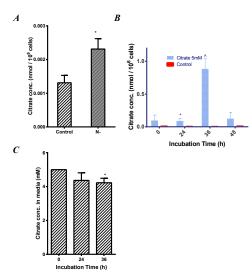


Figure 3.3: Change of citrate concentration over time. *: p < 0.05 and ^: p < 0.01. A. Effect of N starvation on the concentration of intracellular citrate. B. Change in citrate concentration in the cells. C. Change in citrate concentration in the media.

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Transcriptome analysis using next-generation RNA sequencing

Quality assurance of RNA-seq experiment differential gene Enrichment and

Summary of overall expression patterns pathway analysis Validation of differential expression with

- 4 Transcriptome analysis using next-generation RNA sequencing
 - 4.1 Quality assurance of RNA-seg experiment
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Transcriptome analysis using next-generation RNA sequencing

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Quality assurance of RNA-seq experiment

- High-quality RNA was isolated with little degradation
- 88% of 168 million raw reads with satisfactory quality mapped to genome
- 19502 of 19526 annotated transcripts were assembled
- 5000 of putative novel isoforms were found

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Transcriptome analysis using next-generation RNA sequencing

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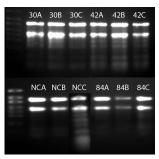


Figure 4.1: RNA gel electrophoresis image. Samples of RNA isolated from cells were check for integrity on a non-denaturing agarose gel. 28S and 18S rRNA were present in the top two bands, respectively, with an approximate density ratio of 2:1. Smear of degraded RNA was not observed.

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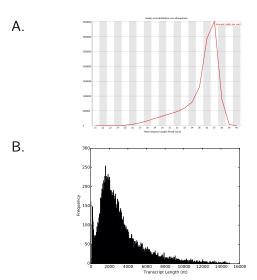


Figure 4.2: Quality check of raw sequencing reads and transcripts. **A.** Quality score distribution over all raw sequencing reads. **B.** Transcript length distribution over the assembly

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Summary of overall differential gene expression patterns

- Criteria: log2FC>2 or log2FC<-2, FDR < 0.01 and total CPM of all samples > 20
- Differentially expressed:
 - 6.24% of transcripts in cells treated with compound 30
 - 7.25% of transcripts in cells treated with compound 42
 - 16.12% of transcripts in cells treated with compound 84

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Table 4.1: Numbers of differentially expressed transcripts

| | Up | Down | Total | Percent change | |
|------------------|------|------|-------|----------------|--|
| 30 | 754 | 462 | 1216 | 6.24% | |
| 42 | 917 | 496 | 1413 | 7.25% | |
| 84 | 1644 | 1500 | 3144 | 16.12% | |
| 30* ¹ | 36 | 53 | 89 | 0.46% | |
| 42* | 51 | 29 | 80 | 0.41% | |
| 84* | 806 | 1029 | 1835 | 9.41% | |
| 30+42* | 69 | 62 | 131 | 0.67% | |
| 30+84* | 36 | 66 | 102 | 0.52% | |
| 42+84* | 183 | 125 | 308 | 1.58% | |
| Common | 613 | 280 | 893 | 4.58% | |

^{1*} indicates that transcripts were differentially expressed only in the condition named in the current row. For example, the row of '42+84*' shows that 183 transcripts are significantly up-regulated in response to 42 and 84 but not 30.

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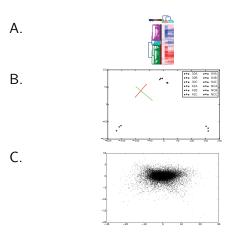


Figure 4.3: Summary of global gene expression profiles. **A.** Heatmap of gene expression relative to control. The log2 fold change of CPM of each sample was plotted.**B.** PCA plot of different conditions. **C.** PCA plot of different genes.

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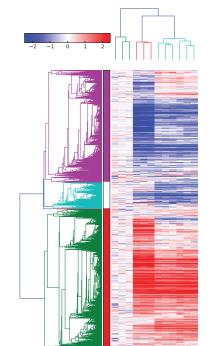
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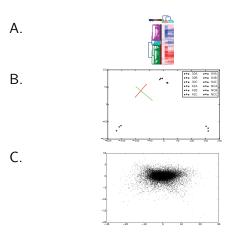


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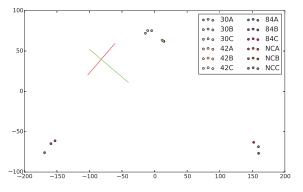
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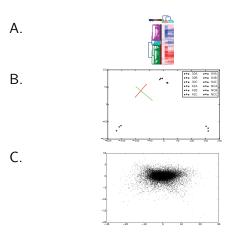


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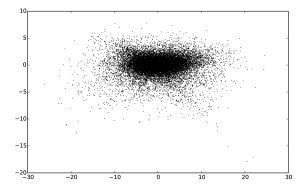
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Validation of differential expression with

Enrichment and pathway analysis

- Gene Set Enrichment Analysis based on GO terms:
 - GO term was assigned to each transcript based on protein domain information or homology
 - Gene sets were created based on these GO terms
- In-depth analysis of pathways related to lipid metabolism
 - Glycolysis
 - TCA cycle
 - Carbon fixation
 - Starch metabolism

 - Fatty acid biosynthesis
 - Lipid metabolism

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Transcriptome analysis using next-generation RNA sequencing Quality assurance of RNA-seq experiment

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Table 4.2: Summary of significantly changed GO categories

| | | | <u> </u> | |
|---|------|----------------------|----------|---------|
| GO term | Size | NES(30) ¹ | NES(42) | NES(84) |
| DNA replication | 47 | 2.76* ² | 2.59* | 2.59* |
| Vesicle-mediated trans- | 44 | 2.29* | 2.26* | 2.10* |
| port | | | | |
| Intracellular protein | 66 | 2.26* | 2.22* | 1.98* |
| transport | | | | |
| Microtubule-based | 77 | 2.17* | 1.62* | 1.78* |
| movement | | | | |
| DNA recombination | 30 | 1.71* | 1.68* | 1.72* |
| ATP hydrolysis coupled | 21 | 1.70* | 1.61* | 1.71* |
| proton transport | | | | |
| $(1 \rightarrow 3)$ - β -D-glucan | 8 | 1.70* | 1.67* | 0.83 |
| biosynthetic process | | | | |
| Glycerol metabolic pro- | 14 | 1.57* | 1.60* | 1.94* |
| cess | | | | |
| Proton transport | 7 | 1.53* | 1.2 | 1.4 |
| tRNA aminoacylation | 39 | 1.51* | 1.97* | 2.26* |
| for protein translation | | 1.01 | 2.5. | 0 |
| Protein ubiquitination | 48 | 1.50* | 1.61* | 1.69* |
| Oxidation-reduction | 475 | 1.15 | 1.24 | 1.39* |
| process | 773 | 1.13 | 1.27 | 1.55 |
| ргоссээ | | | | |

¹Normalized enrichment score for the condition specified. A positive score indicates up-regulation of the named gene set.

^{2*} indicates nominal p < 0.05 and FDR < 0.25.

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Transcriptome analysis using next-generation RNA sequencing Quality assurance of RNA-seq experiment Summary of overall differential gene expression patterns Enrichment and pathway analysis Validation of differential expression with qPCR

(continued)

| (22.12.11.22.2) | | | | | | | |
|-----------------|--|--|--|--|--|--|--|
| Size | NES(30) | NES(42) | NES(84) | | | | |
| 30 | -2.72* | -2.47* | -2.39* | | | | |
| | | | | | | | |
| 181 | -2.52* | -2.50* | -2.76* | | | | |
| | | | | | | | |
| 187 | -2.41* | -2.36* | -2.66* | | | | |
| | | | | | | | |
| 255 | -1.91* | -2.27* | -1.54* | | | | |
| 30 | -1.90* | -2.17* | -2.37* | | | | |
| | | | | | | | |
| 41 | -1.83* | -1.57* | -2.14* | | | | |
| 13 | -1.74* | -1.51* | -1.45 | | | | |
| | | | | | | | |
| 13 | -1.55* | -1.25 | -1.29 | | | | |
| 39 | -1.22 | -1.07 | -1.71* | | | | |
| 9 | -1.45 | -1.63* | -0.49 | | | | |
| | | | | | | | |
| 9 | -1.46 | -1.56 | -1.71* | | | | |
| | 30 181 187 255 30 41 13 13 39 9 | 30 -2.72* 181 -2.52* 187 -2.41* 255 -1.91* 30 -1.90* 41 -1.83* 13 -1.74* 13 -1.55* 39 -1.22 9 -1.45 | 30 -2.72* -2.47* 181 -2.52* -2.50* 187 -2.41* -2.36* 255 -1.91* -2.27* 30 -1.90* -2.17* 41 -1.83* -1.57* 13 -1.74* -1.51* 13 -1.55* -1.25 39 -1.22 -1.07 9 -1.45 -1.63* | | | | |

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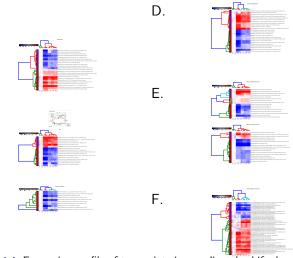


Figure 4.4: Expression profile of transcripts in coordinately shifted major metabolic pathways. Annotated transcripts encoding enzymes involved in specific pathways with total CPM > 10 and FDR < 0.01 in at least one condition were selected for analysis. **A.** Glycolysis. **B.** TCA cycle. **C.** Carbon fixation. **D.** Starch metabolism. **E.** Fatty acid biosynthesis **F.** Lipid metabolism

Glycolysis ACS3IAcetvi-CoA synthetase (EC 6.2.1.1); Acetate-CoA lil ^metabolic process DLD2||^oxidation-reduction process|cell redox homeostasis PYK3|Pyruvate kinase (PK) [EC 2.7.1.40]; catalyses the |^glycolytic process FBA1/Fructose-1.6-bisphosphate Aldolase: Aldehyde-Ivasel *glycolytic process DLA2IDihydrolipoamide acetyltransferase (EC 2.3.1.12), I^metabolic process Cre01.q055408|AMP-binding, conserved site, AMP-dependent synthet| metabolic process Cre16.g677450|Glucose-6-phosphate 1-epimerase, Glycoside hydrola|^carbohydrate metabolic process PYK5|Pyruvate kinase (PK) [EC 2.7.1.40]| "glycolytic_process PDH2|Putative Pyruvate dehydrogenase (lippamide): pyruvl ^ metabolic process PGI1|Phosphoglucose isomerase (PGI), phosphohexose isoml^glycolytic process GAPN1|Glyceraldehyde 3-phosphate dehydrogenase, nonphosp|^oxidation-reduction process AEP1|Putative aldose-1-epimerase (EC 5.1.3.3) (aldose m|^carbohydrate_metabolic_process HXK1/Hexokinase: catalyses the ATP-dependent conversion/^carbohydrate metabolic process Cre07.g347100|Aldose 1-/Glucose-6-phosphate 1-epimerase, Galactol ^ carbohydrate metabolic process PGH1|Enolase (ENO); phosphoenolpyruvate hydratase; 2-phl^qlycolytic process PDC3|Pyruvate decarboxylase [EC 4.1.1.1]; requires thia ADH1IDual function alcohol dehydrogenase / acetaldehydel ^oxidation-reduction process PYK4IPvruvate kinase (PK) [EC 2.7.1.40]; catalyses the Inglycolytic process GAP1|Glyceraldehyde 3-phosphate dehydrogenase (EC 1.2.1|^oxidation-reduction process PFK1|Putative phosphofructokinase family protein (EC 2.|^glycolytic process PFK2|Phosphofructokinase family protein (EC 2.7.1.11 or| "glycolytic_process GPM1|Phosphoglucomutase, plastid form; glucose phosphom|^carbohydrate_metabolic_process

DLA1|Dihydrolipoamide acetyltransferase, probably mitocl ^metabolic process

Transcriptional
Response of
Chlamydomonas
reinhardtii to
Small
Lipid-Inducing
Molecules
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Transcriptome analysis using next-generation

В.

Quality assurance of RNA-seq experiment Summary of overall differential gene expression patterns Enrichment and pathway analysis Validation of differential expression with qPCR

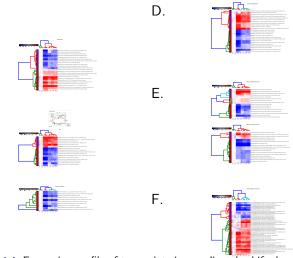
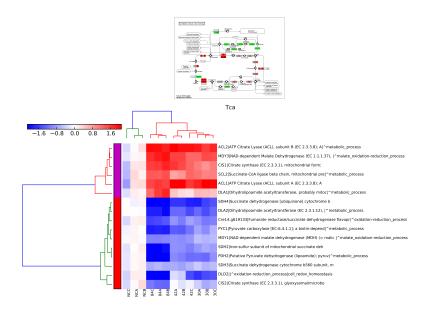


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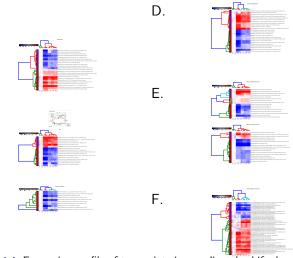
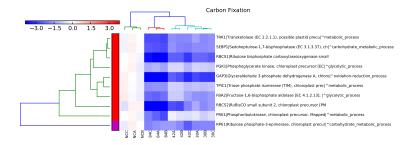


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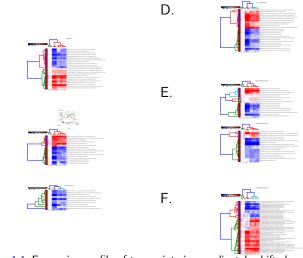
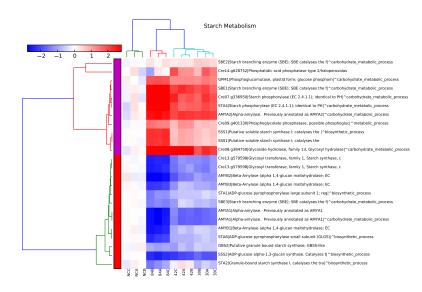


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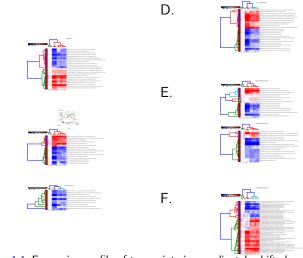
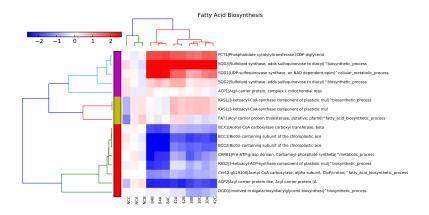


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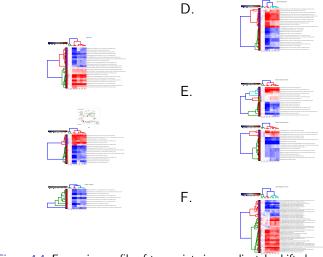
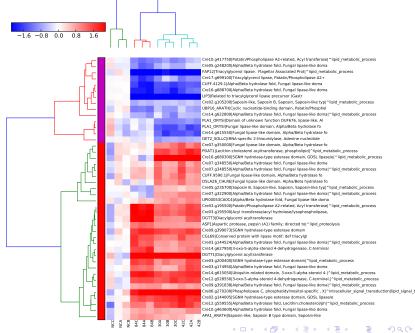


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Lipid Metabolic Process



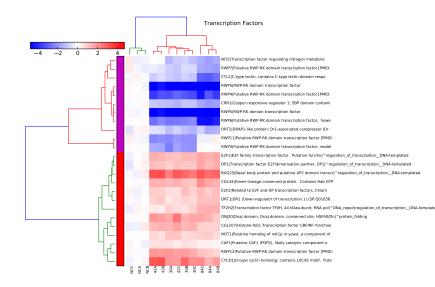


Figure 4.5: Expression profile of transcription factors. Annotated transcripts encoding transcription factors with total CPM > 10 and FDR < 0.01 in at least one condition were selected for analysis.

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Transcriptome analysis using next-generation RNA sequencing

Quality assurance of RNA-seq experiment
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4 Transcriptome analysis using next-generation RNA sequencing

- 4.1 Quality assurance of RNA-seq experiment
- 4.2 Summary of overall differential gene expression patterns
- 4.3 Enrichment and pathway analysis
- 4.4 Validation of differential expression with qPCR

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Transcriptome analysis using next-generation RNA sequencing

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Validation of differential expression with qPCR

- 4 genes of interest expressed at different levels were selected
- Results from RNA-seq are comparable to qPCR data

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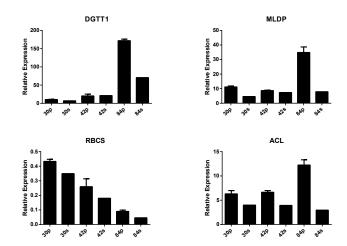


Figure 4.6: Comparison of the expression of selected genes using qPCR. In qPCR measurements (indicated with suffix "p"), relative expression is the fold change of each condition relative to control (N+) normalized with the relative expression of reference gene RACK1. In RNA-seq measurements (indicated with suffix "s"), relative expression is the fold change of CPM in each condition relative to control.

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Discussion

Effects of compounds on lipid accumulation and growth

Advantages and limitations of RNA-sea and computational methods

Overview of the transcriptional responses leading to TAG accumulation Cell signaling and transcription regulation

Future directions

5 Discussion

- 5.1 Effects of compounds on lipid accumulation and growth
- 5.2 Advantages and limitations of RNA-seq and computational methods
- 5.3 Overview of the transcriptional responses leading to TAG accumulation
- 5.4 Cell signaling and transcription regulation
- 5.5 Future directions

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Effects of compounds on lipid accumulation and growth

- Four selected compounds induce significant increase in TAG accumulation in *Chlamydomonas reinhardtii* without severe impact on growth
- Compound 84 induced a 6-fold increase in lipid droplet accumulation
- Compound 30, 42 and 67 induced 3- to 5-fold increase
- Except for compound 84, growth reduction was only between 11% to 18%
- Cells were treated with 20 μM of each compound. EC50: 5 μM

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Advantages and limitations of RNA-seq and computational methods

- Illumina HiSeq: affordable cost and high reliability. 30 million reads for each sample: 100 bp single-end
- Computational tools were carefully selected based on the efficiency and suitability of the algorithms
- 19502 out of 19526 annotated transcripts were detected
- 5335 putative novel transcripts were also assembled
- Alternative splicing analysis was not performed as pair-end reads were not used

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Overview of the transcriptional responses leading to TAG accumulation

- Metabolic fluxes are channeled to TAG accumulation in a mechanism distinct from nitrogen starvation
- Carbon flow from glycolysis: fermentation > TCA cycle
- ACS3 ↓, encoding acetyl-CoA synthase. Genes in starch catabolism ↑
- Citrate efflux from TCA cycle contributes to fatty acid biosynthesis
- Turnover of SQDG and PG but not DGDG may play important role in TAG accumulation
- Strong suppression of genes encoding TAG lipases

Discussio

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Cell signaling and transcription regulation

- RWP-RK domain TFs, regulators of nitrogen responses and gametogenesis ↓: e.g. NIT2
- SBP domain TFs, regulators of fatty acid and lipid biosynthesis ↓: e.g. NRR1
- TFs regulating cell cycle progression ↑
- NIT2 $\downarrow \rightarrow$ NIA1 $\downarrow \rightarrow$ NO₃⁻ \uparrow
- SAC3 $\uparrow \rightarrow$ ASR1/3 $\uparrow \rightarrow$ SO₄ $^- \uparrow$

Discussio

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Future directions

Future directions

- Biological processes on protein and metabolite level: targeted proteomics and metabolics
- Lipid trafficking and biosynthetic process: lipidomics
- Cell signaling cascade: protein phosphorylation and small effectors
- Direct target identification: protein-ligand interaction