

Analysis of differential gene expression in wild and cultivated rice under drought stress

Ingo Giebel¹

¹Math.-Nat. Fakultät, Heinrich-Heine-Universität Düsseldorf

¹QBio304: Applied Bioinformatics

²RG Network Analysis and Modelling, Leibniz Institute of Plant Genetics and Crop Plant Research

²IBG-4: Bioinformatik, Forschungszentrum Jülich GmbH

¹Prof. Dr. Björn Usadel

²Dr. Jedrzej Jakub Szymanski

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Contents

1	Abstract	3
2	Introduction	3
3	Materials and methods	3
3.1	Selection of the RNA-seq data	3
3.2	Quality evaluation	3
3.3	RNA-seq preprocessing	4
3.4	Transcripts abundances quantification	4
3.5	Statistical evaluation and differential expression analysis	6
3.5.1	Import of the kallisto transcript-level estimates	6
3.5.2	Filtering and normalization	7
3.5.3	Hierarchical cluster analysis	8
3.5.4	Principal component analysis	8
3.5.5	Identification of differentially expressed genes	10
3.6	Functional enrichment analysis	10
4	Results	10
4.1	Quality evaluation	10
4.2	Reads mapped to the reference transcriptome	11
4.3	Hierarchical cluster analysis	11
4.4	Principal component analysis	11
4.5	Differentially expressed genes	14
4.6	Functional enrichment analysis	18
5	Discussion	18
6	Online content and license notice	20
	References	21
	Index	23

List of Figures

1	Exemplary FastQC quality assessment of the per base sequence content - raw vs trimmed FASTQ file	5
2	Exemplary FastQC quality assessment of the per base sequence quality - raw vs trimmed FASTQ file	5
3	TPM statistics about the imported kallisto data	7
4	Log2(CPM) distribution of the unfiltered, non-normalized data	7
5	Log2(CPM) distribution of the filtered, non-normalized data	8
6	Log2(CPM) distribution of the filtered, normalized data	8
7	Log2(CPM) distribution of the filtered, normalized data in comparison with the non-normalized and the unfiltered data	9
8	Trimmomatic preprocessing	11
9	FastQC quality assessment of the preprocessed FASTQ files	12
10	kallisto pseudoalignments	12
11	Hierarchical cluster analysis of the <i>O. nivara</i> RNA-seq data	13
12	Hierarchical cluster analysis of the <i>O. sativa</i> RNA-seq data	13
13	PCA of the log2(CPM) data - <i>O. nivara</i>	14
14	PCA of the log2(CPM) data - <i>O. sativa</i>	15
15	Volcano plot of the DEGs - <i>O. nivara</i>	15
16	Volcano plot of the DEGs - <i>O. sativa</i>	16
17	Venn diagrams of the DEGs	16
18	Heatmap of the DEGs - <i>O. nivara</i>	17
19	Heatmap of the DEGs - <i>O. sativa</i>	17
20	Manhattan plot with the first 10 top-ranked GO terms highlighted - <i>O. nivara</i>	19
21	Manhattan plot with the first 10 top-ranked GO terms highlighted - <i>O. sativa</i>	19

List of Tables

1	Number of genes with no reads, and number of genes with CPMs ≥ 1 . . .	7
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1 Abstract

TODO: Provide a brief summary of the purpose of the assignment, the methods used, the main findings, and the significance of the results. Limit the abstract to 200-250 words.

2 Introduction

RNA-sequencing is used to analyze the transcriptome, indicating which of the genes encoded in the DNA are turned on or off and to what extent. This study examines the impact of drought stress on the gene expression of wild and cultivated rice, using statistical methods. To this end, publicly available RNA-seq data from the Institute of Botany, Chinese Academy of Sciences, submitted on January 1st, 2021, is analyzed with respect to differential gene expression. This data allows for a direct comparison of normal and drought stress conditions for two closely related rice species: wild rice (*Oryza nivara*), and cultivated rice (*Oryza sativa*). Furthermore, it allows for the comparison of the two wild rice cultivars BJ278 and BJ89.

3 Materials and methods

3.1 Selection of the RNA-seq data

This study uses publicly available paired-end RNA-seq data of wild and cultivated rice, submitted in January 1, 2021 by the Institute of Botany, Chinese Academy of Sciences. This data allows to compare rice grown under normal conditions with rice grown under drought stress conditions. Furthermore, the data allows for an interspecies comparison of wild rice (*Oryza nivara*, cultivars BJ278 and BJ89) with cultivated rice (*Oryza sativa*, cultivar Nipponbare).

All samples were uniformly taken from seedlings (leaf tissue) at the age of twelve days. Used sequencing platform: Illumina HiSeq 2000.

All this makes the data well suited for a targeted analysis of drought stress responses.

3.2 Quality evaluation

The quality of the raw and trimmed RNA-seq data was assessed using FastQC ("Babraham Bioinformatics," 2023). FastQC is a quality control analysis tool for high throughput sequencing data. It provides information about

- *basic statistics*: some simple composition statistics for the FASTQ file analyzed
- *per base sequence quality*: an overview of the range of quality values across all bases at each position in the FASTQ file

- *per tile sequence quality*: an overview of the per tile sequence quality in case an Illumina library was used
- *per sequence quality scores*: an overview of how the overall quality scores of the sequences are distributed
- *per base sequence content*: an overview of the proportion of each base position in a FASTQ file for which each of the four normal DNA bases has been called
- *per sequence GC content*: the GC content across the whole length of each sequence in a file compared with a normal distributed GC content
- *per base N content*: an overview of the N content at each position across all bases
- *sequence length distribution*: an overview of how the sequence lengths are distributed
- *sequence duplication levels*: an overview of the degree of duplication for every sequence in a library
- *over-represented sequences*: a list of over-represented sequences matched against common contaminants
- *adapter content*: a check for significant amounts of adapter sequences the FASTQ file

The results of the separate FastQC analyses (of the raw and trimmed FASTQ files), the results of the Trimmomatic trimming and the information about the kallisto pseudoalignments were summarized in an interactive MultiQC HTML-report. See (Ewels et al., 2016).

3.3 RNA-seq preprocessing

The initial quality assessment of the raw FASTQ files revealed that about roughly the first 12 base pairs of the reads were of low quality. Therefore, the data was preprocessed/trimmed using Trimmomatic, a "flexible and efficient preprocessing tool, which could correctly handle paired-end data" (Ewels et al., 2016).

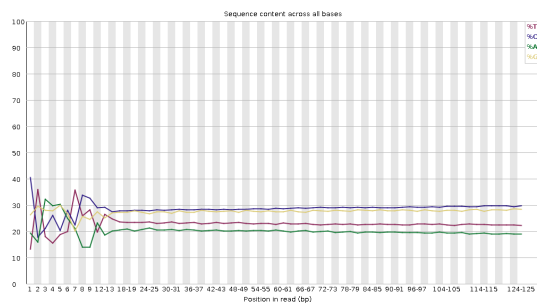
That trimming substantially improved the per base sequence content and the per base sequence quality. Figures 1 and 2 show exemplarily a comparison of the FastQC assessments of a raw FASTQ file vs the corresponding trimmed FASTQ file.

3.4 Transcripts abundances quantification

The mapping/pseudoalignment of the RNA-seq reads and the abundances quantification of the transcripts was done using kallisto. According to (Bray et al., 2016), kallisto offers the following advantages over other alignment and quantification software:

Figure 1: FastQC quality assessment of the per base sequence content of the raw FASTQ file CRR240976_f1.fastq.gz vs the trimmed file CRR240976_f1.trim.p.fastq.gz

i) Raw data



ii) Trimmed data

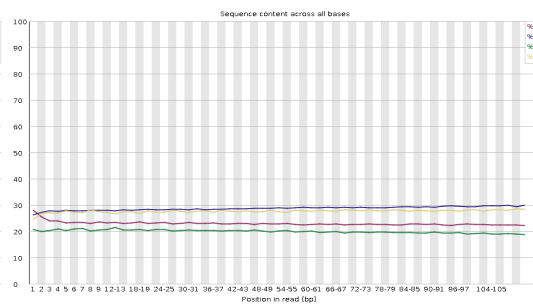
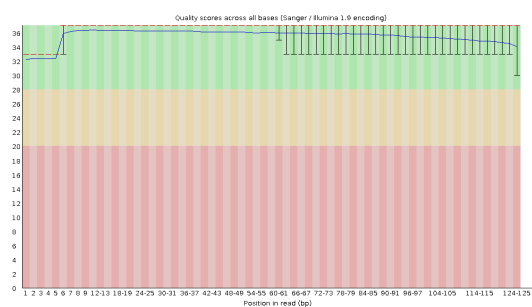
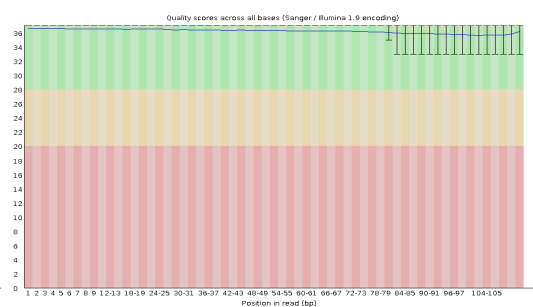


Figure 2: FastQC quality assessment of the per base sequence quality of the raw FASTQ file CRR240976_f1.fastq.gz vs the trimmed file CRR240976_f1.trim.p.fastq.gz

i) Raw data



ii) Trimmed data



kallisto is a program for quantifying abundances of transcripts from RNA-Seq data, or more generally of target sequences using high-throughput sequencing reads. It is based on the novel idea of pseudoalignment for rapidly determining the compatibility of reads with targets, without the need for alignment. On benchmarks with standard RNA-Seq data, kallisto can quantify 30 million human bulk RNA-seq reads in less than 3 minutes on a Mac desktop computer using only the read sequences and a transcriptome index that itself takes than 10 minutes to build. Pseudoalignment of reads preserves the key information needed for quantification, and kallisto is therefore not only fast, but also comparably accurate to other existing quantification tools. In fact, because the pseudoalignment procedure is robust to errors in the reads, in many benchmarks kallisto significantly outperforms existing tools.

kallisto requires a reference genome/transcriptome for aligning the RNA-seq data. To this end, reference FASTA cDNA dumps of *Oryza nivara*, cultivar BJ278 and *Oryza sativa*, cultivar Nipponbare were downloaded from Ensembl. The Ensembl project delivers reference data for genome interpretation for any species: genome assemblies from public archive are annotated with genes, regulatory regions, variants and comparative data to provide a foundation for scientific research and genome interpretation (Cunningham et al., 2021).

3.5 Statistical evaluation and differential expression analysis

The preprocessed and aligned data was further evaluated and analyzed using an R-script (R Core Team, 2023) executed within RStudio (Posit team, 2023). The following sections describe the analysis steps in detail.

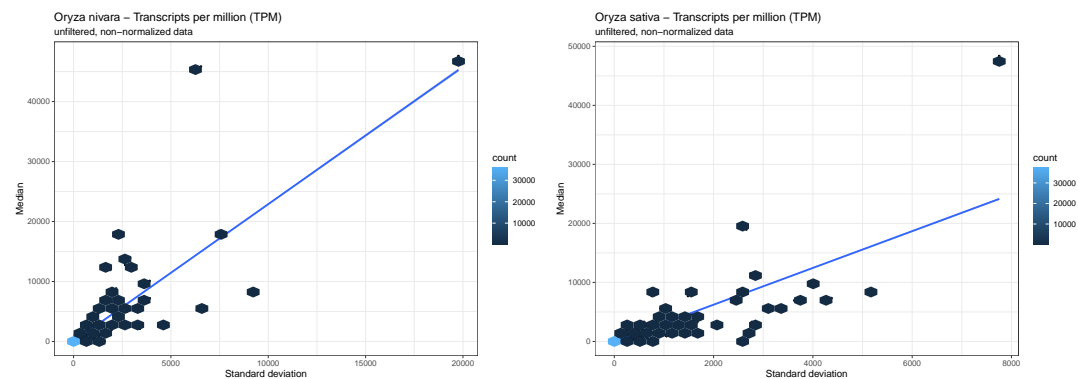
3.5.1 Import of the kallisto transcript-level estimates

The kallisto transcript-level estimates were imported using the R-package `tximport` (Love et al., 2022; Soneson et al., 2015). Thereby, the abundances, counts, and transcript lengths were summarized to the gene level.

Scaling method: average transcript length over samples and then the library size (parameter `lengthScaledTPM`).

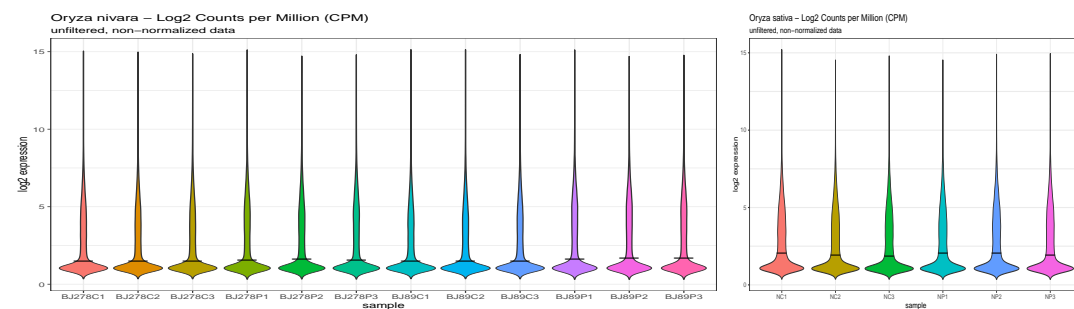
The mapping of the transcript IDs (used within the kallisto `abundance.tsv` files) to the corresponding gene IDs was done using the BioMart database `plants_mart` hosted at <https://plants.ensembl.org>. Datasets: `nivara_eg_gene` and `osativa_eg_gene` for *O. nivara* and *O. sativa*, respectively. See (Durinck & Huber, 2023; Durinck et al., 2009).

Figure 3 shows some basic transcripts per million (TPM) statistics about the imported kallisto files.

Figure 3: TPM statistics about the imported kallisto data

3.5.2 Filtering and normalization

For further analysis, `DGEList`-objects with counts per million (CPM) and $\log_2(\text{CPM})$ values were created using the R-package `edgeR` (Chen et al., 2023; Robinson et al., 2010). Figure 4 shows the distribution of the $\log_2(\text{CPM})$ values.

Figure 4: $\log_2(\text{CPM})$ distribution of the unfiltered, non-normalized data

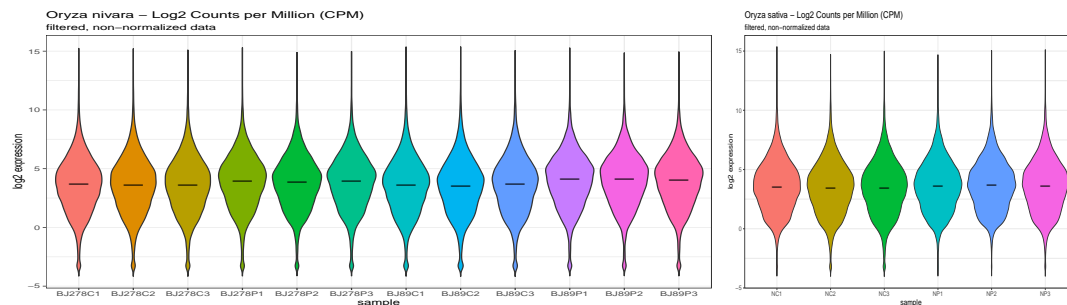
In order to assess reasonable values for filtering the data, the number of genes with no reads at all (in none of the samples) and conversely the number of genes with CPMs ≥ 1 in at least 1, 2, 3, ... of the samples were computed. Table 1 summarizes the results.

Table 1: Number of genes with no reads at all, and conversely number of genes with CPMs ≥ 1 in at least $n = 1, 2, 3, \dots$ of the samples

Species	Σ genes	Σ no reads	Genes with CPMs ≥ 1 in at least n samples					
			1	2	3	4	5	6
<i>O. nivara</i>	36313	7115	21001	20355	19891	19302	18895	18481
<i>O. sativa</i>	37967	4699	23934	22510	21609	20592	19715	18656

Filtering out genes with low reads (< 1 CPM in at least half of the samples) resulted in the distribution of the $\log_2(\text{CPM})$ values shown in figure 5.

Figure 5: $\log_2(\text{CPM})$ distribution of the filtered (< 1 CPM in at least half of the samples), non-normalized data



Finally, the filtered data was normalized using the `edgeR` function `calcNormFactors` which calculates scaling factors to convert raw library sizes into effective library sizes. Used normalization method: TMM. The results of the normalization are shown in figure 6.

Figure 6: $\log_2(\text{CPM})$ distribution of the filtered, normalized data

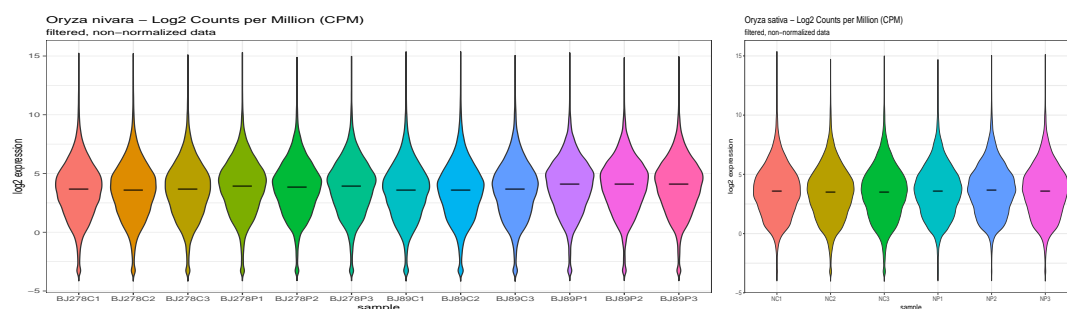


Figure 7 provides an overview of the filtering and normalization results.

3.5.3 Hierarchical cluster analysis

A hierarchical cluster analysis (HCA) was performed via the `stats` function `hclust` on the Euclidean distance matrix of the $\log_2(\text{CPM})$ values. Used agglomeration method: `method = complete`.

3.5.4 Principal component analysis

A principal component analysis (PCA) of the filtered and normalized $\log_2(\text{CPM})$ values was performed via the `stats` function `prcomp`.

A *Oryza nivara* – Log2 CPM
unfiltered, non-normalized data

log2 expression

sample

B *Oryza sativa* – Log2 CPM
unfiltered, non-normalized data

log2 expression

sample

C *Oryza nivara* – Log2 CPM
filtered, non-normalized data

log2 expression

sample

D *Oryza sativa* – Log2 CPM
filtered, non-normalized data

log2 expression

sample

E *Oryza nivara* – Log2 CPM
filtered, normalized data

log2 expression

sample

F *Oryza sativa* – Log2 CPM
filtered, normalized data

log2 expression

sample

3.5.5 Identification of differentially expressed genes

In order to identify differentially expressed genes (DEGs), design and contrast matrices were created using the `stats` function `model.matrix` and the `limma` function `makeContrasts`.

The design matrices were used to create linear model fits for each gene via the `limma` functions `voom` and `lmFit`.

The linear model fits and the contrast matrices were used to calculate estimated coefficients and standard errors (contrasts) via the `limma` function `contrasts.fit`.

The contrasts were used to "calculate moderated t-statistics, moderated F-statistic, and log-odds of differential expression by empirical Bayes moderation of the standard errors towards a global value" (empirical Bayes statistics) via the `limma` function `eBayes` (Smyth et al., 2023).

Finally, the empirical Bayes statistics were used to extract a table of the top-ranked genes via the `limma` function `topTable` (sorted by the `LogFC`-values).

Venn diagrams of the DEGs (according to the calculated empirical Bayes statistics) were created via the `gprofiler2` function `decideTests` (with parameters `method = "global"`, `adjust.method = "BH"`, `p.value = 0.01`, `lfc = 7`) and the `limma` function `vennDiagram`.

See (Ritchie et al., 2015) for details on the statistical foundations implemented by `limma`.

3.6 Functional enrichment analysis

A functional enrichment analysis of the 100 "top-ranked" genes was performed via the `gprofiler2` function `gost` (with `correction_method = "fdr"`) (Kolberg & Raudvere, 2021).

4 Results

4.1 Quality evaluation

The RNA-seq data was initially assessed with FastQC, and according to this assessment the data was preprocessed/trimmed with Trimmomatic and afterwards assessed again with FastQC. Finally, an overall report on the data preprocessing, the quality assessments and the kallisto pseudoalignments was created with MultiQC.

Figure 8 shows the MultiQC report on the Trimmomatic preprocessing (the surviving reads).

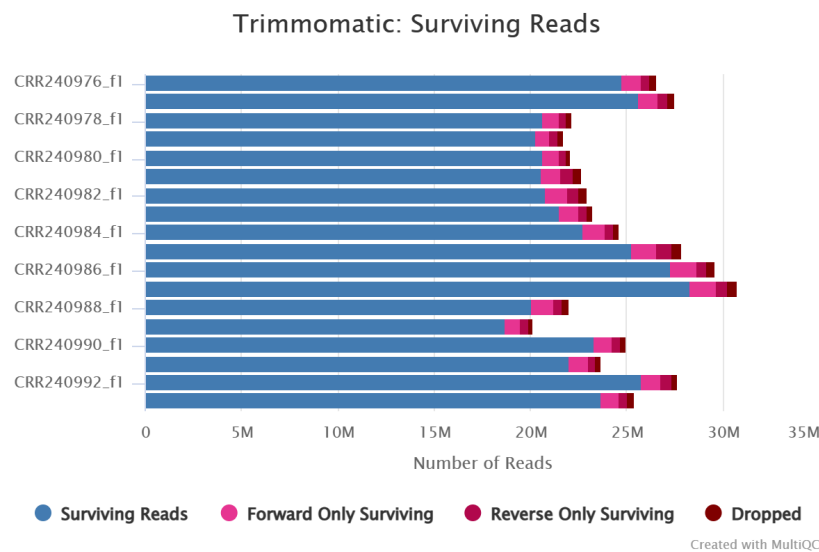
Figure 8: Trimmomatic preprocessing

Figure 9 shows the MultiQC overview of the FastQC quality assessments of the trimmed FASTQ files.

According to these quality assessments, the (trimmed) RNA-seq data may be regarded as good quality for the purpose of this research.

4.2 Reads mapped to the reference transcriptome

For most of the FASTQ files, kallisto pseudoaligned well above 80 % of the (preprocessed) RNA-seq reads. Figure 10 shows a MultiQC overview of the kallisto pseudoalignments.

4.3 Hierarchical cluster analysis

The hierarchical cluster analysis reveals that the normal condition groups and the drought stress condition groups are closely related (grouped together). But the data for *O. nivara* also shows that the cultivar has an even greater impact on the clustering than the drought stress condition (see figures 11 and 12).

4.4 Principal component analysis

The principal component analysis (PCA) reveals that for both *O. nivara* and *O. sativa* the first two principal components account for more than 80 % of the variance in the gene expression. Figures 13 and 14 show the contribution percentage of the samples to the first two principal components (PCs) for the two species.

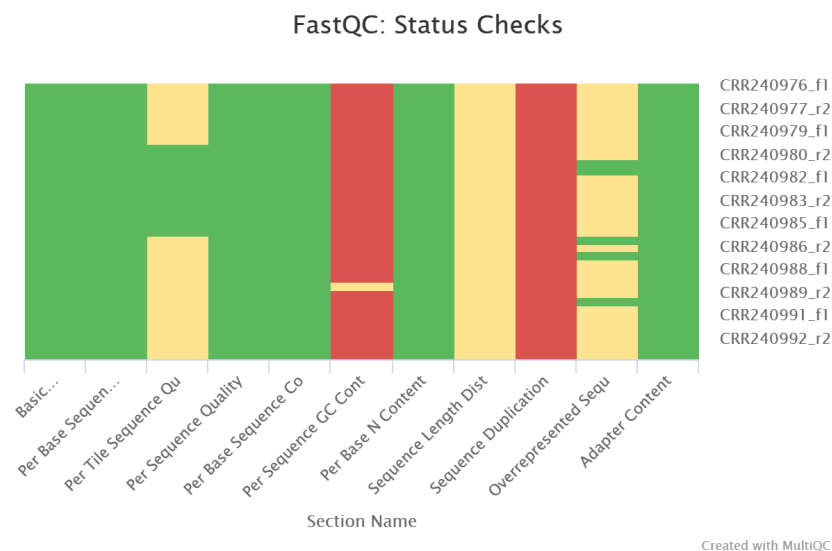
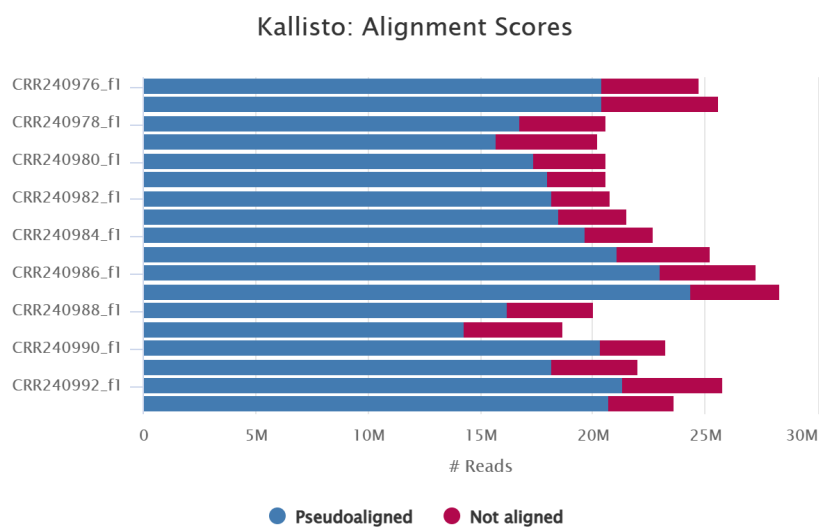
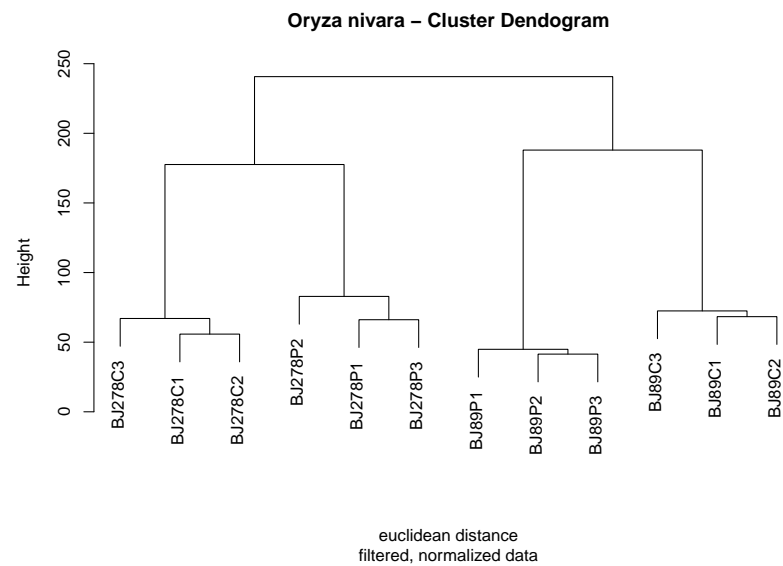
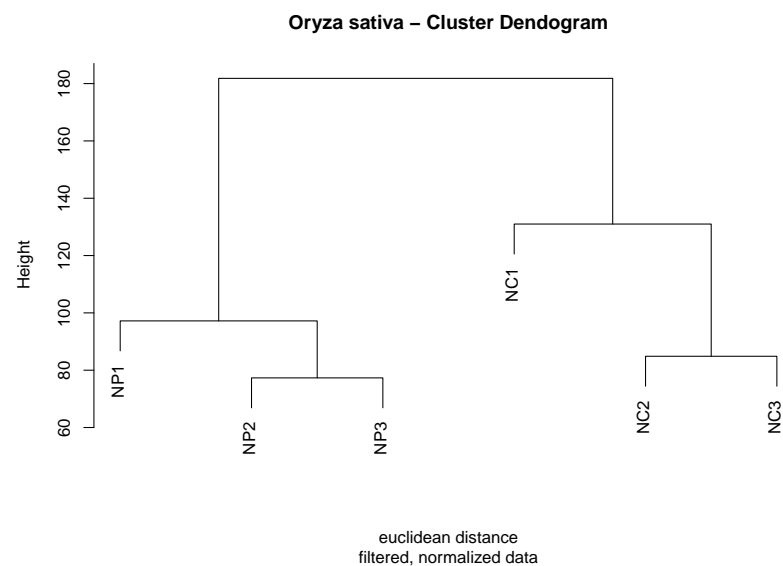
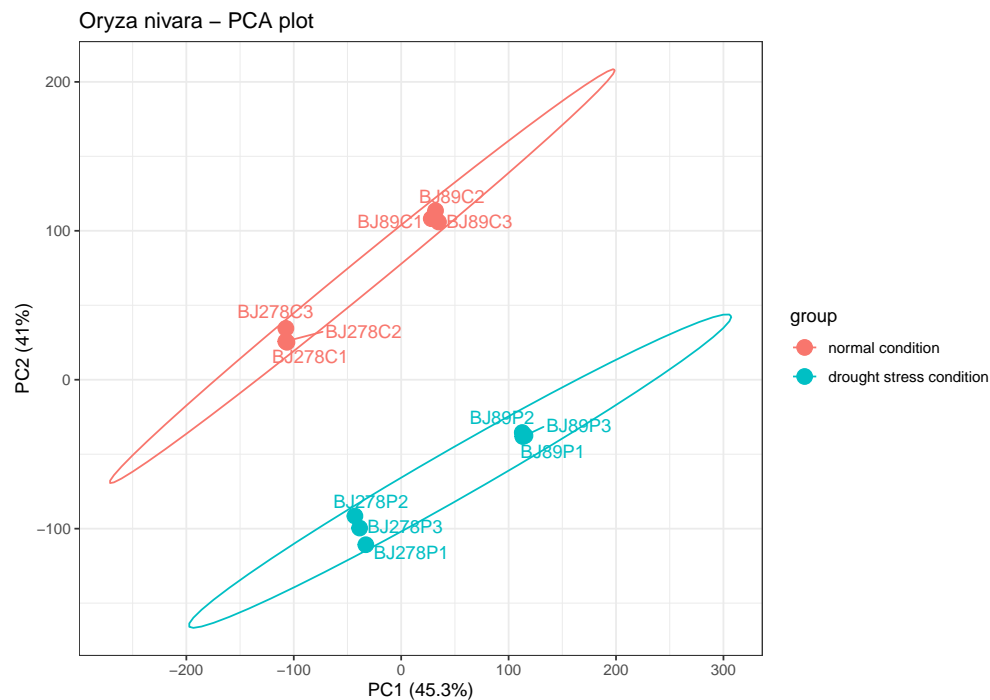
Figure 9: FastQC quality assessment of the preprocessed FASTQ files**Figure 10:** kallisto pseudoalignments

Figure 11: Hierarchical cluster analysis of the *O. nivara* RNA-seq data**Figure 12:** Hierarchical cluster analysis of the *O. sativa* RNA-seq data

For *O. nivara*, the samples from the same condition (normal vs drought stress) cluster together, with a tight clustering of the two different cultivars. This means that the different conditions might well explain the differences in gene expression, with the cultivar being an important confounding factor.

For *O. sativa*, the samples from the same condition cluster together with the exception of sample "NC1". This might be due to a batch effect.

Figure 13: PCA of the log2(CPM) data - *O. nivara*



4.5 Differentially expressed genes

The volcano plots 15 and 16 provide a quick overview of the genes with large fold changes that are also statistically significant. These may be the biologically most significant genes.

According to the limma tests with a p-value of one percent, there are 15 down- vs 33 up-regulated genes for *O. nivara* under drought stress conditions, and 2 down- vs 16 up-regulated for *O. sativa*. Figure 17 shows the respective Venn diagrams. Figures 18 and 19 present heatmaps of these genes.

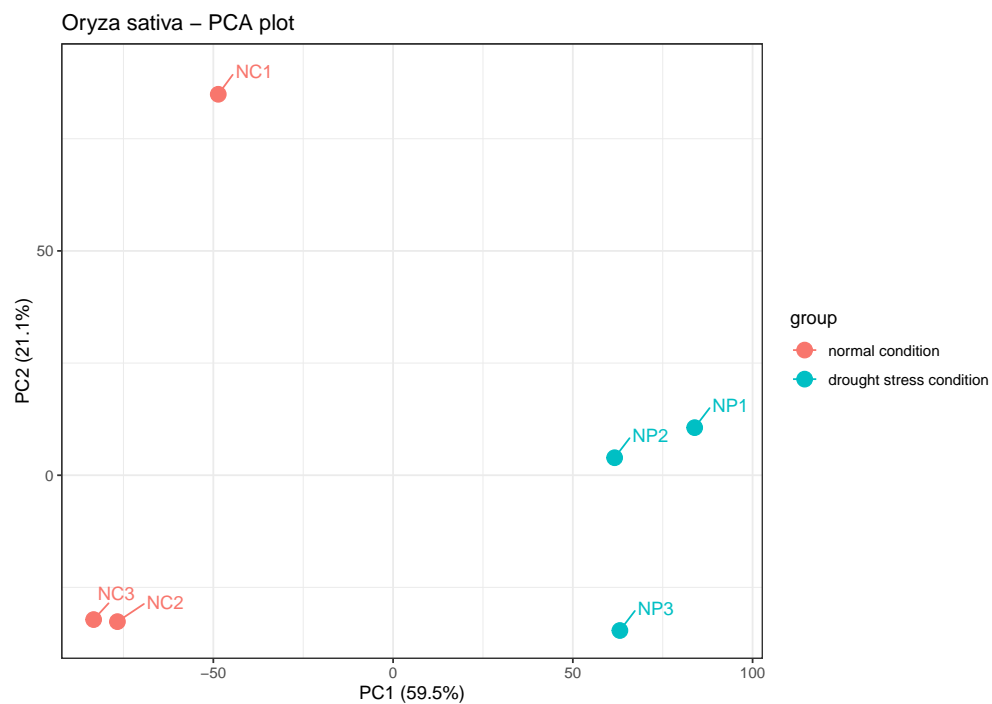
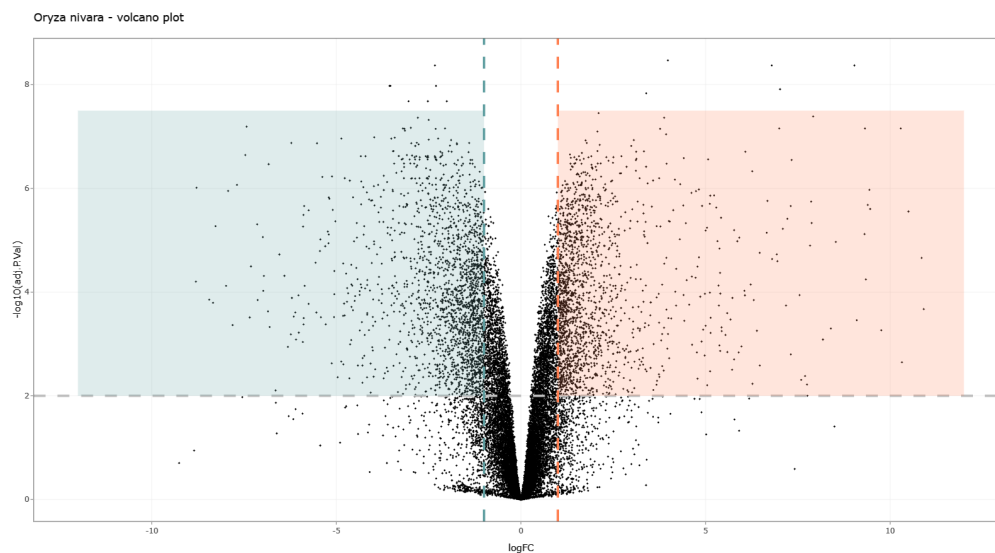
Figure 14: PCA of the log₂(CPM) data - *O. sativa***Figure 15:** Volcano plot of the DEGs - *O. nivara*

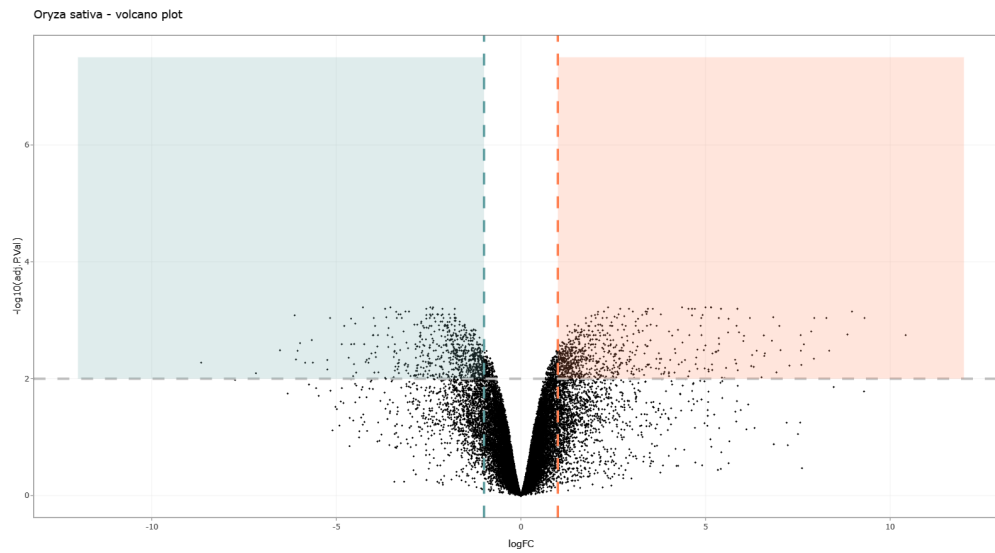
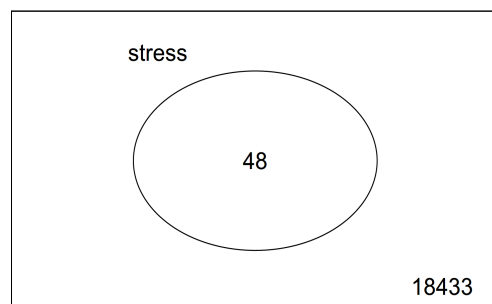
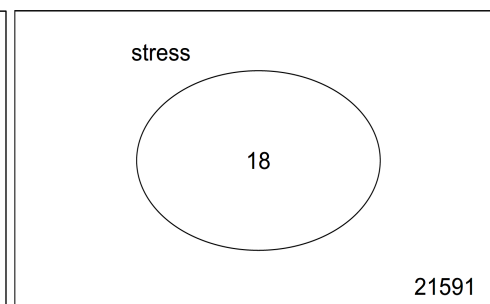
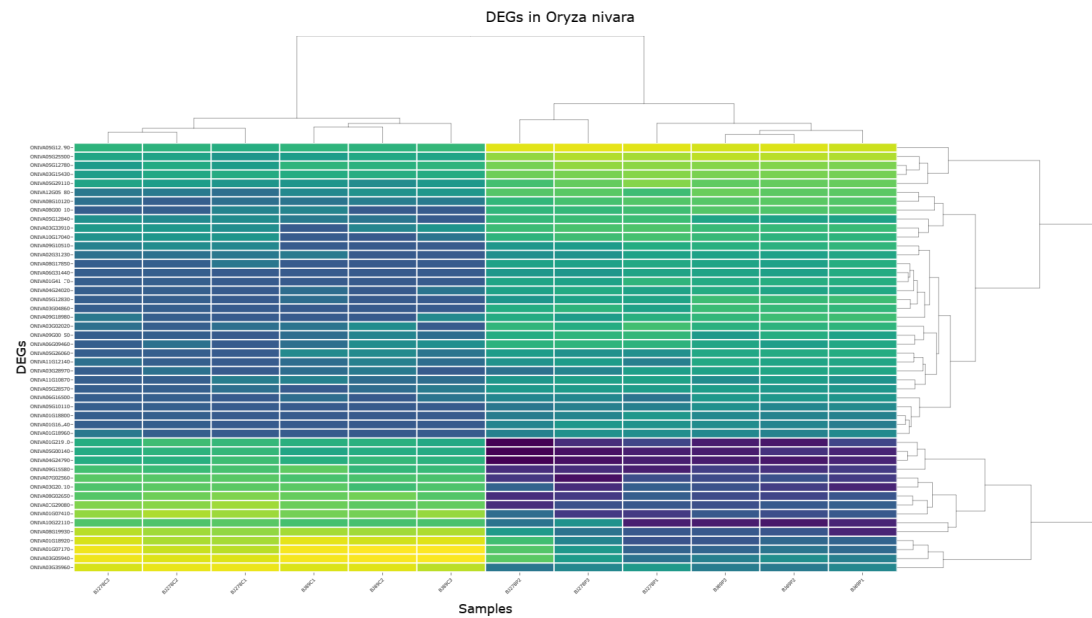
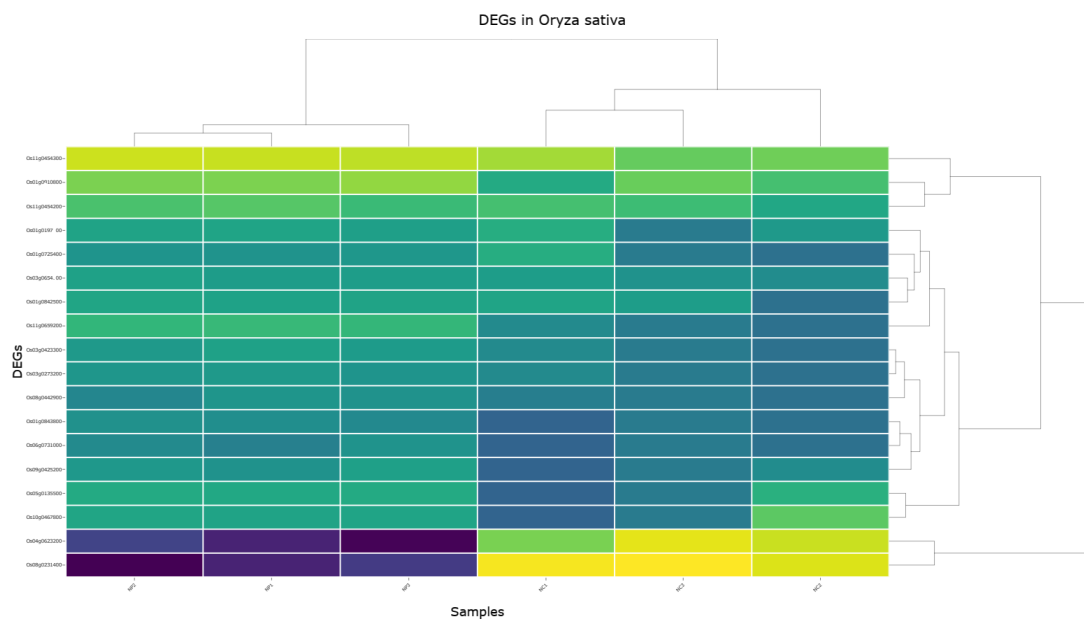
Figure 16: Volcano plot of the DEGs - *O. sativa***Figure 17:** Venn diagrams of the DEGsi) *O. nivara*ii) *O. sativa*

Figure 18: Heatmap of the DEGs - *O. nivara***Figure 19:** Heatmap of the DEGs - *O. sativa*

Down- and up-regulated genes are for *O. nivara*:

ONIVA01G07170, ONIVA01G07410, ONIVA01G16640, ONIVA01G18800, ONIVA01G18920, ONIVA01G18960, ONIVA01G21950, ONIVA01G41350, ONIVA02G31230, ONIVA03G02020, ONIVA03G04860, ONIVA03G05940, ONIVA03G15430, ONIVA03G20710, ONIVA03G28970, ONIVA03G33910, ONIVA03G35960, ONIVA04G24020, ONIVA04G24790, ONIVA05G00140, ONIVA05G10110, ONIVA05G12780, ONIVA05G12790, ONIVA05G12830, ONIVA05G12840, ONIVA05G25500, ONIVA05G26060, ONIVA05G28570, ONIVA05G29080, ONIVA05G29110, ONIVA06G09460, ONIVA06G16500, ONIVA06G31440, ONIVA07G02560, ONIVA08G00310, ONIVA08G02650, ONIVA08G10120, ONIVA08G17850, ONIVA08G19930, ONIVA09G00350, ONIVA09G10510, ONIVA09G15580, ONIVA09G18980, ONIVA10G17040, ONIVA10G22110, ONIVA11G10870, ONIVA11G12140, ONIVA12G05380

For *O. sativa* these genes are:

Os01g0197700, Os01g0725400, Os01g0842500, Os01g0843800, Os01g0910800, Os03g0273200, Os03g0423300, Os03g0654700, Os04g0623200, Os05g0135500, Os06g0731000, Os08g0231400, Os08g0442900, Os09g0425200, Os10g0467800, Os11g0454200, Os11g0454300, Os11g0659200

A description and the location of all these genes can be found at <https://plants.ensembl.org>. For a deeper analysis of these genes and their potential biological significance, the available information appears to be insufficient.

4.6 Functional enrichment analysis

Finally, for the one-hundred top-ranked genes a statistical functional enrichment analysis was performed to identify over- or under-represented information from gene ontology (GO) terms. Figures 20 and 21 present the results as Manhattan plots.

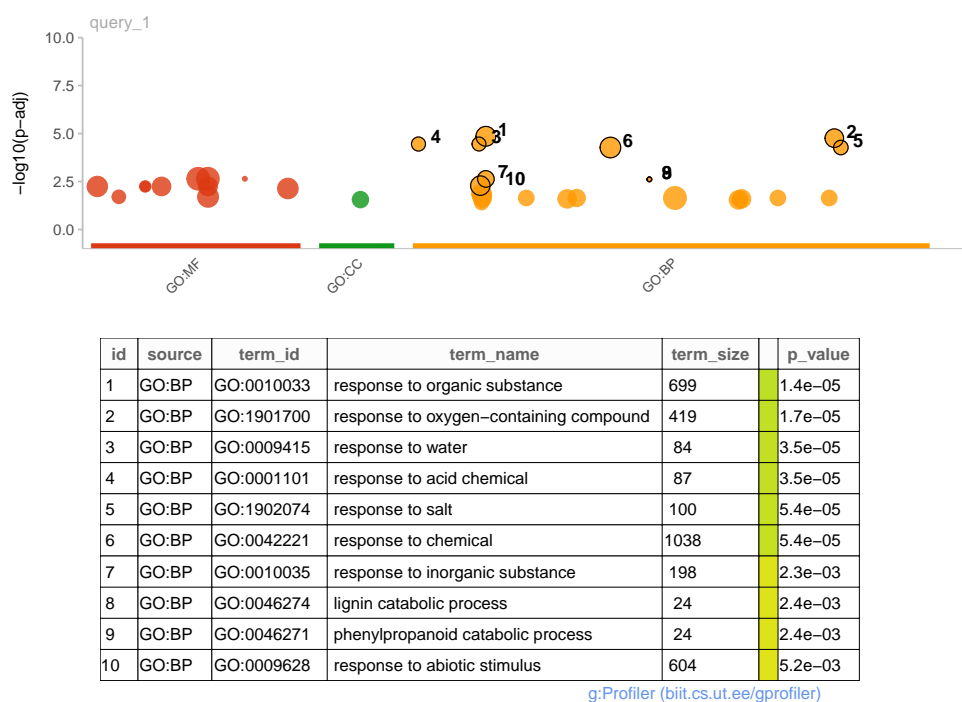
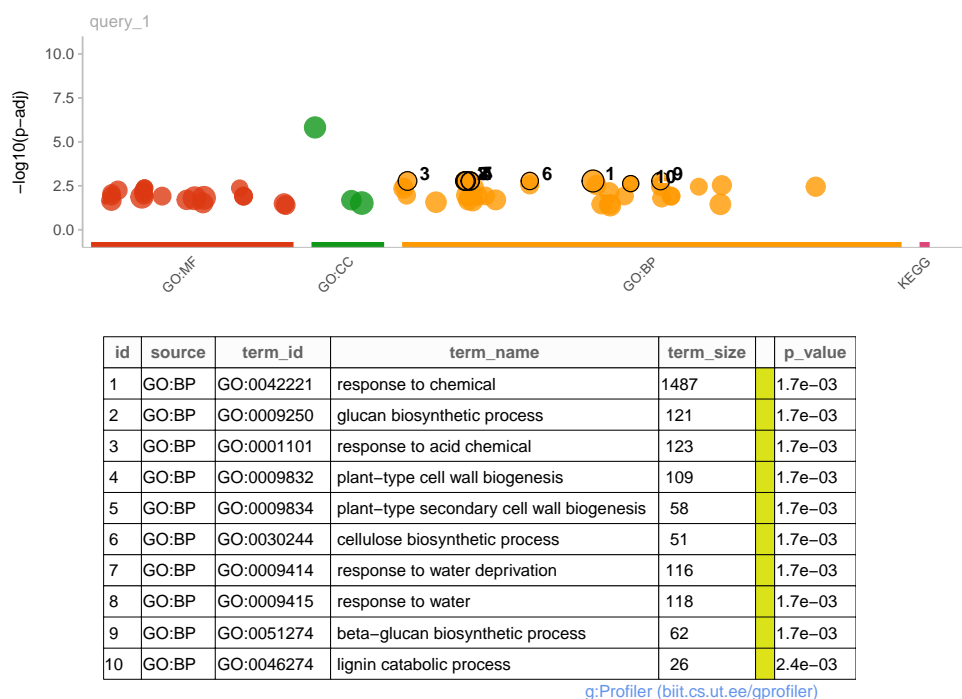
For both *O. nivara* and *O. sativa*, the top ten GO terms belong to the major subontology "biological process (BP)". It appears that the impact of drought stress may - on the gene level - be best described and categorized in terms of biological processes as opposed to the molecular functions (MF) of the genes and the cellular components (CC) in which the gene products are physically located.

Furthermore, for both rice species the following GO terms are significantly enriched (when just comparing the top ten GO terms): response to organic substance, response to water, response to acid chemical, response to salt, response to chemical, lignin catabolic process, phenylpropanoid catabolic process. This confirms the close relationship of the two species, and it also confirms that the GO terms are suitable to describe genetic responses to environmental factors.

5 Discussion

TODO:

Critical evaluation of the results: Discuss the quality and reliability of the RNA-seq data and the downstream analyses.

Figure 20: Manhattan plot with the first 10 top-ranked GO terms highlighted - *O. nivara***Figure 21:** Manhattan plot with the first 10 top-ranked GO terms highlighted - *O. sativa*

Biological implications: Discuss the potential implications of the findings for plant biology and the broader scientific community.

Limitations and future directions: Address the limitations of the current analysis and suggest possible future directions to expand on the findings.

Conclusion: Summarize the main findings of the assignment, reiterating the significance of the results, and provide a final statement on the overall outcome of the study.

6 Online content and license notice

This document, its \LaTeX source files, all figures and tables and all supplemental R and shell scripts are available at the public GitHub repository <https://github.com/IngoGiebel/qbio304-student-work>. Furthermore, the data subfolder contains the following files:

- the `abundance.tsv` files created by kallisto
- the `*_fastqc.html` report files created by FastQC
- the log-files created by Trimmomatic and kallisto
- the study design file for the data: `studydesign-PRJCA004229.tsv`

The data folder does not contain: the raw and trimmed FASTQ files, the reference genome files for *O. nivara* and *O. sativa*, the index files for these reference genomes created by kallisto, the `*_fastqc.zip` files created by MultiQC. Information on how to get this data is provided in the `README.md` of the data subfolder.

The `README.md` of the scripts subfolder contains information about the external programs required to execute the shell scripts.

This work, its \LaTeX source files, all figures and tables and all provided R and shell scripts are under the MIT License: <https://github.com/IngoGiebel/qbio304-student-work/blob/main/LICENSE.md>.

References

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Index

B

batch effect, 14

C

counts per million (CPM), 7

cultivar

- BJ278, 3
- BJ89, 3
- Nipponbare, 3

D

DNA

- cDNA, 6

differentially expressed genes (DEGs),
10

E

Ensembl, 6

F

FASTA, 6

FASTQ, 3

FastQC, 3, 10f

functional enrichment analysis, 10, 18

G

gene

- ID, 6

gene ontology (GO), 18

- biological process (BP), 18
- cellular component (CC), 18
- molecular function (MF), 18

genome/transcriptome

- reference, 6

H

hierarchical cluster analysis (HCA), 8, 11

- Euclidean distance matrix, 8

I

Illumina

- HiSeq 2000, 3

K

kallisto, 4, 10f

L

LogFC, 10

M

MultiQC, 4, 10

O

Oryza

- nivara, 3
- sativa, 3

P

principal component analysis (PCA), 8,
11

- principal component (PC), 11

R

R, 6

- RStudio, 6
- package
 - edgeR, 7
 - gprofiler2, 10
 - limma, 10
 - stats, 8, 10
 - tximport, 6

RNA-seq, 3

- adapter sequence, 4
- contaminant, 4
- quality assessment, 3

T

transcript

- ID, 6
- abundances quantification, 4
- pseudoalignment, 4
- transcripts per million (TPM), 6

transcriptome, 3

Trimmomatic, 4, 10