TITLE: PEO: Plant Expression Omnibus - a comparative transcriptomic database for 103
Archaeplastida

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Abstract

The Plant Expression Omnibus (PEO) is a web application that provides biologists with
access to gene expression insights across over 100 plant species, ~60,000 manually
annotated RNA-seq samples, and more than four million genes. The tool allows users to
explore the expression patterns of genes across different organs, identify organ-specific
genes, and discover top co-expressed genes for any gene of interest. PEO also provides
functional annotations for each gene, allowing for the identification of genetic modules
and pathways. PEO is designed to facilitate comparative kingdom-wide gene expression
analysis and provide a valuable resource for plant biology research. We provide two case
studies to demonstrate the utility of PEO in identifying candidate genes in pollen coat
biosynthesis and investigating the biosynthetic pathway components of capsaicin in
Capsicum annuum. The database is freely available at https://expression.plant.tools/.

Introduction

The earliest members of the plant kingdom evolved circa one billion years ago from photosynthetic algae. The archetypical characteristics we associate with plants, such as seeds, roots, leaves, flowers, and wood, were evolutionary innovations that allowed plants to colonize diverse habitats successfully. Today, plants form an indispensable component of life on Earth as the primary food producer in the terrestrial ecosystem. Plants being mostly sessile, have also had to evolve means of adapting quickly to their local environments. These adaptations came in the form of complex regulatory and metabolic pathways, which we are now only beginning to unravel.

Studying plant biology and genetics will allow us to improve desirable traits and engineer crops that provide higher yield and/or are more tolerant to various environmental stresses (Niazian, 2019; Nowicka et al., 2018). The use of plants as a source of various medicinal components is also exemplified in the extraction of the analgesic salicins from willow bark or the antimalarial artemisinin from *Artemisia annua* (Desborough and Keeling, 2017; Krishna et al., 2008). The elucidation of biosynthetic pathways of these medicinal compounds could then be harnessed for large-scale production and modification in recombinant systems (Cravens et al., 2019; Paddon et al., 2013; Sabzehzari et al., 2020). Currently, the study of plant gene function requires the characterization of individual genes and their interactors and regulators, which are typically limited to a handful of model plants. Consequently, bioinformatic approaches that integrate genomic, transcriptomic, metabolomic, and phenotypic data have been developed to accelerate the process of gene function prediction (Hansen et al., 2018; Radivojac et al., 2013; Rhee and Mutwil, 2014).

Studying gene co-expression can effectively address this, given the "guilt-by-association" principle, where genes with similar expression are likely to have similar functions (Rhee and Mutwil, 2014). Co-expression analysis allows one to transfer functional annotation to unannotated genes, predict undiscovered members of metabolic pathways, and identify regulator-target relationships (Rao and Dixon, 2019). Plant organs have signature gene expression patterns and similar profiles between organs are correlated to the similarity in function of the organs (Ma et al., 2005). Moreover, many genes exhibiting organ-specific expression are found to be conserved across land

plants (Julca et al., 2021). Consequently, a gene's expression profile across organs can

provide clues to a gene's function. For example, two genes that show similar gene

expression profiles across different organs and tissues are likely to be part of the same

protein complex (Persson et al., 2005) or biosynthetic pathway (Delli-Ponti et al., 2021)

or to be targeted to the same subcellular compartment (Ryngajllo et al., 2011).

Over the last decade, sequencing cost has been falling faster than Moore's law

(Wetterstrand, 2013), giving rise to immense volumes of plant genomic and transcriptomic

data. Many online databases with diverse functionalities and plant species have emerged

to provide analytical and visualization tools for the scientific community (Lim et al., 2022).

However, no existing database has been designed to cover gene expression for more

than 20 species. We believe that the full value of RNA-seq repositories is only realized

when insights are accessible to biologists working on the genes, including non-model

species. We created a user-friendly tool to help non-programmer biologists extract

insights about their gene of interest from big data (Tan et al., 2020). A web application to

access gene expression knowledge on any gene would be needed to provide an effortless

and instantaneous experience for biologists, which requires large volumes of processed

data. While the data is publicly available, the interfaces have not been specifically

designed for bulk data acquisition for whole kingdoms. We addressed this by designing

a parallel-processing pipeline to automatically discover, download and process RNA-seq

data for the whole plant kingdom in less than a month (Goh and Mutwil, 2021), making

the provision and maintenance of a kingdom-wide resource feasible.

Here, we developed the Plant Gene Expression Omnibus (PEO,

https://expression.plant.tools), a web application to provide an interface for biologists to

access gene expression insights across >100 plant species. Specifically, the tool

addresses how a gene is expressed across different organs, whether it displays organ-

specific expression patterns and identifies top organ-specific genes for each organ. The

tool also automatically provides a list of the highest correlated genes based on the

Pearson Correlation Coefficient for any gene of interest, negating the need for separate

analysis. In addition, Pfam and Mapman annotations have also been linked to each gene,

allowing for functional searches to identify genetic modules or pathways. The software

design considers scalability, with the ability to include more species, other expression

conditions, and other gene annotations. The project lays the architectural foundations for

a kingdom-wide gene expression analysis resource.

Methods

Data source

Supplemental Table S1 details the sources of raw files used and contributors. These were

then reorganized into the upload format described in Supplemental Table S2, using

custom Python scripts. A total of 103 species were included. The complete list is available

in Supplemental Dataset S1. To obtain the TPM matrices, RNA-seq transcripts were

obtained from public databases via our pipeline (Goh and Mutwil, 2021). Gene expression

was quantified as transcript per million (TPM) via pseudoalignment to reference coding

sequences (CDS) of each species, using kallisto (Bray et al., 2016). Organ annotations

were done by manually mapping samples to Plant Ontology (PO) terms, which are precise

and consistent references to plant anatomical entities across species (Walls et al., 2019).

Genes were functionally annotated with Mapman annotations via Mercator

(Schwacke et al., 2019) for four representative species and were assigned to the

remaining species via sequence similarity score from diamond (Buchfink et al., 2015).

Mapman was chosen over Gene Ontology (GO) as it is specific to plant pathways and

processes (Klie and Nikoloski, 2012). Genes were also annotated with protein families

(Pfam) (Mistry et al., 2021). Gene identifiers were standardized to the versions in TPM

matrices, and alternative isoforms were excluded.

Database schema and software architecture

The schema defines how data is modeled and stored in our document-oriented

database and can be described with an entity relational diagram (ERD) (Supplemental

Figure S1). The chosen database technology is MongoDB, a document-oriented

database allowing flexible data modeling to optimize our specific read patterns. This is

more suitable than relational databases that enforce data schema normalization, which

would incur expensive join operations on every read. The database is hosted serverless

on MongoDB Atlas, on AWS.

Figure 1: RNA sequencing contents of the Plant Expression Omnibus (PEO)
database. A) The heatmap shows the relative abundance of RNA-seq data for the
different species (columns) and organs, tissues, and cell types (rows). The numbers in
paratheses in rows indicate the number of species that have data for a given plant
structure. The cell opacity indicates the relative abundance of RNA-seq samples across

130   organs for each species. B) The treemap showing the relative number of RNA-seq
131   samples for the different species. The areas of the rectangles correspond to the number
132   of samples, which is given in parentheses.
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Results and discussion
Querying the Plant Expression Omnibus (PEO)
PEO is an interlinked database that includes 103 species, 4.6 million genes, 5,760
Mapman terms, 7,566 Pfam terms and 59,856 quality-controlled samples, of which
41,592 are annotated with 78 PO terms. To our knowledge, no species-wide gene
expression database exists for many of these 103 species. The distribution of data
illustrating species composition and organ specificity are presented as a treemap and
heatmap, respectively (Figure 1). Not surprisingly, leaves were the most sampled plant
organs (97 species contain leaf samples), followed by roots (81), flowers (70), stems (67)
and seeds (49)(Figure 1A). The less represented samples represent structures not found
in all flowering plants (strobilus, tuber, protonema, spore) or samples that are difficult to
collect (trichome, zygote, egg cell). *Arabidopsis thaliana* had the highest number of RNA-
seq samples (Ara.th, 72,732), followed by maize (35,309), rice (25,090), wheat (14,137)
and other crops (Figure 1B), with the next model organism *Brachypodium distachyon* on
the 17th place with 3,004 samples. The annotation depth of Mapman, Pfam and Plant
Ontology annotations are also provided (Supplemental Figure S2). The data are sorted
by several modes, such as species type, organ specificity, as well as Mapman and Pfam
annotation. Such an arrangement allows the user to query for gene expression in specific
organs of interest or look for orthologous genes in non-model species. Sequence-based
BLAST and annotation-based Pfam searches can be used to identify homologous and
orthologous genes of interest across the database. Together with Mapman annotation
and organ specificity predictions, putative functions can be ascribed to gene orthologues.
Finally, PEO also provides a list of top co-expressed genes for any gene of interest for all
species present in the database, allowing for the discovery of specific metabolic or

developmental pathways that are spatiotemporally regulated.

Figure 2: Frontend of Gene Expression Omnibus. A) Genes of interest are searchable via GeneID, protein sequence, Pfam domains, and species as query entries. Browsing of various databases is available in the above tabs. B) Example search by organ type (Pollen). C) The output displays a list of genes known to be present in a specific organ of interest, searchable by species.

The home page of PEO consists of several search modes. Queries can be based
on specific GeneID or protein sequences. It is also possible to browse the database via
the 'Species', 'Organs', 'Pfam', or 'Mapman' annotations (Figure 2). For example, we can
select the 'Organs' tab, which provides a list of Plant Ontology (PO) terms. By selecting
'Pollen' as our organ of interest, we arrive at a page displaying a set of transcripts sorted
by SPM. This specificity measurement ranges between zero and one, where one
indicates the gene is exclusively expressed in the tissue (Julca et al., 2021). The page
also provides information on the Median and Mean Transcripts per Million (TPM) values
used to calculate SPM value and the number of samples the calculations are based on.
Mapman annotations are also listed for individual transcripts to provide information on
putative gene functions. This database can also be searched by species to obtain the
pollen-specific genes in other species present in the PEO.

As another example of a query strategy, we also show an example search using
the protein sequence of the Arabidopsis gene ABORTED MICROSPORES
(*AT2G16910*), a transcription factor known to be associated with the regulation of pollen
formation (Xu et al., 2014). The search output provides a list of genes sorted by %identity,
with further information on E-values, bit scores, number of mismatches, and gap
openings. The gene list includes matched genes from the other species present in PEO,
providing a means to discover gene orthologues from less common organisms
(Supplemental Figure S3).

Clicking on a gene of interest in the list (AMS, *AT2G16910*), brings us to a gene
page containing relevant information on this gene (Figure 3). The top of the page provides
information about the GeneID, Species name, and TaxonID. The next section displays
the putative organ specificity of the gene of interest based on SPM calculations. Details
on the values that the SPM calculation is based on is present in the grey subtext below
the SPM value. The top organs are reported with mean TPM, standard deviation, and
median TPM, showing the magnitude of expression. Since genes with low TPM values
can appear to be specifically expressed due to noisy expression, the mean TPM values
can be used to flag such genes (Proost and Mutwil, 2018). The sample size is also
reported. Together, these support user interpretation of whether the gene displays organ-
specific expression. The data can be visualized in a bar chart or box/scatterplot format.

Figure 3: Example gene page of the gene of interest (*AT2G16910*). A) The gene page provides organ specificity of the gene predicted by the SPM score. B) It also displays relative transcript expression in various plant organs/tissues as a box plot or bar chart. Moving the mouse pointer over the points in the box plot shows the corresponding experiment ID. C) Mapman and Pfam annotations for the gene of interest are displayed

to provide information on gene function. D) A list of top co-expressed genes sorted by

PCC value.

The boxplots depict quartiles and whiskers (hover to reveal values), indicating the skew

of data. PEO allows for automatic rescaling to exclude the outliers for the y-axis (Figure

3). Manual zooming and panning is also available by the control bar at the right of each

chart. The charts are available to download in .png or .svg image formats, with the raw

data also available for download in tsv format. Associated Pfam and Mapman annotations

are also provided, with the relevant Mapman bin codes and Pfam names and identifiers

available for reference. Lastly, a list of top-coexpressed genes sorted by Pearson

Correlation Coefficient (PCC) is provided for the user.

Use case 1: Identification of genes involved in pollen coat biosynthesis

Here, we provide a case study on how PEO can be used to identify candidate genes in

pollen coat biosynthesis by using PEO and correlation with other evidence available in

the literature. As a starting point, we will use ABORTED MICROSPORES (AMS,

AT2G16910), a transcription factor known to regulate pollen coat biosynthesis (Xu et al.,

2014). The pollen coat is a multilayered structure that provides protection for the nascent

male gametophytes from external stresses (Scott et al., 2004). The outer layer, called

exine, is composed primarily of a polymer called sporopollenin, which is a composite of

fatty acids, phenylpropanoids, phenolics, and carotenoids (Ahlers et al., 1999). It was

found that the *ams* null mutant failed to produce functional pollen, and further

investigations led to its identification as a master regulator of various aspects of pollen

biosynthesis (Xu et al., 2014).

Using PEO, we first looked at the gene page of AMS, which showed its highly

specific expression in the anthers (Figure 4). Next, we obtained the list of top co-

expressed genes against *AMS* and used it to compare against gene clusters identified by

FlowerNet. FlowerNet is a flower-specific database based on microarray data focusing

on stamen-, pollen-, or flower-specific expression (Pearce et al., 2015). By generating a

correlation network, FlowerNet generates gene clusters of transcriptionally coregulated

genes, and based on analysis of tissue specificity and expression at different pollen

maturation stages, we were able to identify several clusters associated with pollen

development. Venn diagram analysis showed that AMS co-expressed genes overlapped
significantly (55%, p = 1.4E-26) with Cluster 37, representing sporopollenin biosynthesis,
but not Clusters 21 and 116, representing pollen exine formation and pollen tube growth,
respectively (Figure 4A). This suggests that *AMS* plays a key role in regulating
sporopollenin biosynthesis in pollen development.

Gene ID	Gene name	Function	Expression
AT1G01280	CYP703A2	cytochrome P450	Anther
AT1G02050	LAP6	Chalcone and stilbene synthase family protein	Anther
AT1G62940	ACOS5	acyl-CoA synthetase	Anther
AT1G69500	CYP704B1	cytochrome P450	Anther
AT3G11980	FAR2	fatty acid reductases	Anther
AT3G13220	ABCG26	ATP-binding cassette transporter G26	Anther
AT3G23770	N.A	O-Glycosyl hydrolases family 17 protein	Anther
AT3G42960	ATA1	homolog of TASSELSEED2	Anther
AT4G14080	MEE48	Involved in the formation of the pollen wall	Anther
AT4G34850	N.A	Chalcone and stilbene synthase family protein	Anther
AT4G35420	DRL1	Dihydroflavonol 4-reductase-like1)	Anther

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239 **Figure 4: Example use case of gene *AMS* (*AT2G16910*), a transcription factor**
240 **known to regulate pollen coat biosynthesis.** A) Gene expression profile by organs

shows its highly specific expression in pollen. Comparison of top co-expressed genes with co-expression clusters extracted from FlowerNet shows strong overlap with Cluster 37 (Sporopollenin biosynthesis) but not Cluster 21 (Pollen exine formation) and Cluster 116 (Pollen tube formation/growth). B) Table shows gene names, functions, and specific expression of genes found in the overlap between AMS co-expression and FlowerNet Cluster 37.

A Discovery of functional orthologues using MapMan and Pfam annotations

B Output: *Solanum lycopersicum*   Output: *Oryza sativa*

Figure 5: Discovery of functional orthologues using MapMan and Pfam annotations. A) Mapman and Pfam annotations for the gene of interest (*AT2G16910*) provide a list of genes annotated with the bins and domains in other species. B) Example output for functional orthologue discovery using MapMan annotation. The gene of

Solanum lycopersicum and *Oryza sativa* show specific expression in reproductive tissues
similar to *AT2G16910* in *Arabidopsis*.

Further examination of the overlapped genes (11 genes) revealed a list of genes
that were annotated as being involved in pollen development (*AT1G01280*, *AT1G69500*,
AT4G35420) or whose mutants were essential for male fertility (*AT1G62940*,
AT3G11980, *AT3G13220*, *AT4G35420*), and were all found to be predominantly
expressed in anthers (Figure 4B, Supplemental Dataset S2). This strategy of using
complementary databases can be used to narrow down large gene lists and identify key
genes involved in a pathway of interest. Finally, using the associated Mapman and Pfam
annotations available on the gene page, we can obtain gene orthologues from other
species and use that as a starting point to investigate genetic pathways in other plants
(Figure 5A). As an example, we examined the genes *SOLYC02G079810.3.1* and
LOC_OS07G36460.1 from *Solanum lycopersicum* and *Oryza sativa*, respectively (Figure
5B). Observations of the respective gene loci of *Solanum lycopersicum* and *Oryza sativa*
show transcript enrichment in reproductive tissues similar to that in Arabidopsis.

Use case 2: Identification of biosynthetic pathway components of capsaicin
Here, we will provide an example of using PEO to investigate capsaicin biosynthesis in
the crop plant *Capsicum annuum*. The genus Capsicum comprises a large class of crop
plants commonly known as peppers (i.e. chili peppers), and its distinctive
pungency/spiciness is due to the alkaloid capsaicin (Suzuki et al., 1980). We looked at
the literature and found that *Pun1* (*CA02G19260*) is a necessary enzymatic component
of capsaicin biosynthesis. The *Pun1* gene encodes an acyltransferase, and the deletion
of the *Pun1* gene in bell peppers is the reason for its distinctive non-pungency compared
to pungent varieties like chili peppers (Stewart Jr et al., 2005). We searched for the *Pun1*
(*CA02G19260*) gene in our database and observed that it was expressed mainly in fruit
and pericarp tissues, consistent with the site of capsaicin accumulation in the plant
(Figure 6A). Next, we obtained the list of top co-expressed genes for *Pun1* and compared
it against a list of putative capsaicin biosynthetic pathway genes previously obtained by
isolation from *Capsicum annuum* fruit tissue at specific developmental stages (Mazourek

et al., 2009; Zhang et al., 2016). This comparison yielded an overlap of 13.7% (7 genes),

which we examined individually for their function and organ expression (Figure 6B). We

observed that all the genes were predominantly found in the pericarp tissue, consistent

with the site of capsaicin accumulation (Figure 6D). We then obtained a putative map of

the capsaicin biosynthetic pathway (Zhang et al., 2016) and attempted to map our gene

list to it. Surprisingly, we observed that most of the genes mapped to the pyruvate-derived

arm of the pathway, suggesting that *Pun1* primarily regulates this arm of capsaicin

biosynthesis (Figure 6C).

Figure 6: Example use case of *Pun1* (*CA02G19260*) from *Capsicum annum*, an

important enzymatic component of capsaicin biosynthesis. A) Gene expression

profile by organs shows its highly specific expression in fruit and pericarp, which is also

the site of capsaicin accumulation. B) Comparison of top co-expressed genes with known
capsaicin biosynthetic pathway components yields an overlap of 13.7% (7 genes). C)
Mapping of genes to proposed capsaicin biosynthetic pathway based on putative gene
function (red boxes). D) Specific expression of the seven genes obtained from PEO.
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Conclusion
We present here a fully annotated Gene Expression Omnibus of 103 plant species, which
provides information on tissue specificity and gene function information of the relevant
gene of interest. PEO also automatically provides a list of top-coexpressed genes for
better elucidation of gene functions and associated pathways. We provided two case
studies of how PEO can be used to study genes and pathways of interest and to narrow
down large putative gene lists based on information on tissue specificity, annotated Pfam
and Mapman functions, and comparison using complementary datasets obtained from
other analyses. These analyses are amenable to any species present in PEO and allow
researchers to build a genetic model of a pathway of interest quickly. As we expand the
number of species available in PEO, we will be able to more effectively empower
researchers working on non-model organisms and more quickly progress the pace of
translational research.
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319

320 **Conflict of interests**
321 The authors declare no conflicts of interest.
322

323 Supplemental Tables:

Data	Content	Prepared by
Species list	Includes list of 103 species, with the sources of their CDS.	Manual curation by Mutwil.
TPM matrices	Quantifies gene expression of each gene in each sample. Each species is represented by a 2D TPM matrix with genes along the rows and samples along the columns.	TPM matrices were processed and compiled from other projects (Goh & Mutwil, 2021; Julca et al., 2021). Villanueva and Mutwil performed quality control.
Organ annotations	Assignment of each RNA-seq sample to a PO term and name.	Manual curation and annotation by Villanueva et. al. (2022, unpublished work).
Mapman annotations	Assignment of each gene to at least one Mapman bin label and name.	Performed in this study by Goh.
Pfam annotations (Interpro)	Assignment of each gene to Pfam domains, which in turn have a name and their associated GO terms.	Manual curation and annotation by Villanueva et. al. (2022, unpublished work).
PEP files	Protein sequence files, required for building the diamond reference db. Diamond (Buchfink et al., 2015) is an alternative to BLAST for fast protein sequence search.	Raw pep files obtained by Villanueva, re-processed by Goh. Diamond protein sequence database was processed by Goh.

325 **Supplemental Table S1:** Raw data collected for PEO

File type	Columns required	Number of files	Constraints
Species list	Taxonomic ID, scientific name, CDS source, CDS url	1 globally	-
TPM matrices	Gene IDs as row index, sample labels as column headers, TPM as values	1 per species	Species must be specified in species list
Gene annotations	Gene annotation label, name any other fields (flexible)	1 per annotation type globally (currently 2, for Mapman and Interpro)	-
Gene annotations assignment	Gene ID, Gene annotation label	1 per species, per annotation type	Genes must exist in TPM matrices, gene annotation must exist in globally defined file
Sample annotations	JSON mapping of sample annotation label (PO terms) to the name of each PO term	1 per sample annotation type globally (1 for PO currently)	-
Sample annotations assignment	Sample label, Sample annotation label (PO term)	1 per species, per sample annotation type	Samples must exist in TPM matrices, sample annotation must exist in globally defined file

327 **Supplemental Table S2:** Processed data files uploaded to PEO

329 Supplemental Figures

Entity Relation Diagram

331 **Supplemental Figure S1: A**rchitectural design of PEO web-tool

333 **Supplemental Figure S2:** Data distribution of PEO showing Mapman, Interpro and Plant

334 Ontology annotation coverage.

Example: Input protein sequence (AT2G16910)

Output: Hits sortable by species and % identity

Omnibus   Species   Organs   PFAM   Mapman   Help

Sequence hits

Gene identifier	Species	Mapman terms	% identity	E-value	Bit score	Alignment length	Mismatches	Gap openings
AT2G16910	Arabidopsis thaliana	RNA biosynthesis.transcriptional regulation.bHLH-type transcription factor, Plant reproduction.gametogenesis.male gametophyt.tapetum development.transcriptional regulator *(DYT1/AMS)	100	0.0	1088	571	0	0
AL3G49670	Arabidopsis lyrata	RNA biosynthesis.transcriptional regulation.bHLH-type transcription factor, Plant reproduction.gametogenesis.male gametophyt.tapetum development.transcriptional regulator *(DYT1/AMS)	97.7	0.0	1064	571	13	0
G23235.T1	Arabidopsis halleri	RNA biosynthesis.transcriptional regulation.bHLH-type transcription factor, Plant reproduction.gametogenesis.male gametophyt.tapetum development.transcriptional regulator *(DYT1/AMS)	95.2	0.0	1039	581	17	3

Supplemental Figure S3: Example search output for protein sequence. Search output

retrieves and sorts candidate orthologous genes from other species available in the

database.

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the Pollen of Torreya californica Torr. (Gymnospermae): Using the 1H-NMR Technique.

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A

B

A

1. Species
Identify genes by species and description
E.g., *Solanum lycopersicum*
Cellulose synthase

2. Organs
Identify organ-specific genes in 103 plant species
E.g., Pollen
Solanum lycopersicum

3. Pfam
Identify genes by Pfam domain ID or description
E.g., PF03552
Cellulose synthase

4. Mapman
Identify genes by biological function
E.g., Bin 21. Cell wall organization
All Mapman bins. Cellulose

5. Gene search
Identify genes by gene ID or protein sequence similarity
E.g.,
At4g32410
LOC_OS01G06450
Protein sequence

B

C

A

B

Gene ID	Gene name	Function	Expression
AT1G01280	CYP703A2	cytochrome P450	Anther
AT1G02050	LAP6	Chalcone and stilbene synthase family protein	Anther
AT1G62940	ACOS5	acyl-CoA synthetase	Anther
AT1G69500	CYP704B1	cytochrome P450	Anther
AT3G11980	FAR2	fatty acid reductases	Anther
AT3G13220	ABCG26	ATP-binding cassette transporter G26	Anther
AT3G23770	N.A	O-Glycosyl hydrolases family 17 protein	Anther
AT3G42960	ATA1	homolog of TASSELSEED2	Anther
AT4G14080	MEE48	Involved in the formation of the pollen wall	Anther
AT4G34850	N.A	Chalcone and stilbene synthase family protein	Anther
AT4G35420	DRL1	Dihydroflavonol 4-reductase-like1)	Anther

A Discovery of functional orthologues using MapMan and Pfam annotations

B Output: *Solanum lycopersicum* Output: *Oryza sativa*

A

C

Figure 8. Putative modles of capsaicin biosynthetic pathway.

B

Pun1 Co-expression   Capsaicin biosynthesis

44   7   128

D

Gene ID	Gene name	Function	Specific expression
CA06G10910	BCKDH E1a	Branched-chain amino acid aminotransferase	Pericarp
CA03G08530	pAMT	Putative aminotransferase	Pericarp
CA01G00840	KasI	Ketoacyl-ACP synthase I	Pericarp
CA11G05940	AT	acyltransferase 1	Pericarp
CA08G18150	ACS	Acyl-CoA synthetase 2	Flower / Pericarp
CA06G26640	FatA	Acyl-ACP thioesterase	Pericarp
CA01G28560	KasIII	Ketoacyl-ACP synthase III	Pericarp