

Choosing reference genes for RT-qPCR for *Fusarium graminearum* plant infection (*In Planta*) and *In Vitro* growth studies based on transcriptomic data

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Background. Choosing reference genes for RT-qPCR for the study of transcriptomic responses of target genes is often done using “standard” reference genes (housekeeping genes) selected before the genomic era. Now, published transcriptome data can be used to aid in this selection to avoid the selection of a reference gene that varies and obscure results.

Methods. We use transcriptome data for the model pathogen fungus *Fusarium graminearum* to select housekeeping genes for *In Vitro* and *In Planta* conditions. Transcriptome data was downloaded from a publicly available database. We selected a database where transcriptome chip data from many experiments using the same chip has been deposited divided the downloaded data into *In Vitro* and *In Planta* conditions based on the information about the experiments.

Results. We ranked the genes with the least variation (relative difference between maximum and minimum expression) across each dataset. Genes previously shown to perform well as reference genes for *In Vitro* conditions in a similar analysis as ours also performed well for *In Vitro* conditions in our dataset but worked less well for *In Planta* conditions. We found 5 reference genes that performed well under both *In Planta* conditions and *In Vitro* conditions.

Discussion. Even if these 5 reference genes performed well, for other (new) target conditions we recommend making a transcriptome analysis to select well performing reference genes for RT-qPCR if possible. Alternatively, select 2 of the 5 genes that we show here performed well under both *In Planta* and *In Vitro* conditions.

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3 ***graminearum* plant infection (*In Planta*) and *In Vitro***
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21 **Abstract**

22 **Background.** Choosing reference genes for RT-qPCR for the study of transcriptomic responses
23 of target genes is often done using “standard” reference genes (housekeeping genes) selected
24 before the genomic era. Now, published transcriptome data can be used to aid in this selection to
25 avoid the selection of a reference gene that varies and obscure results.

26 **Methods.** We use transcriptome data for the model pathogen fungus *Fusarium graminearum* to
27 select housekeeping genes for *In Vitro* and *In Planta* conditions. Transcriptome data was
28 downloaded from a publicly available database. We selected a database where transcriptome
29 chip data from many experiments using the same chip has been deposited divided the
30 downloaded data into *In Vitro* and *In Planta* conditions based on the information about the
31 experiments.

32 **Results.** We ranked the genes with the least variation (relative difference between maximum and
33 minimum expression) across each dataset. Genes previously shown to perform well as reference
34 genes for *In Vitro* conditions in a similar analysis as ours also performed well for *In Vitro*
35 conditions in our dataset but worked less well for *In Planta* conditions. We found 5 reference
36 genes that performed well under both *In Planta* conditions and *In Vitro* conditions.

37 **Discussion.** Even if these 5 reference genes performed well, for other (new) target conditions we
38 recommend making a transcriptome analysis to select well performing reference genes for RT-

39 qPCR if possible. Alternatively, select 2 of the 5 genes that we show here performed well under
40 both *In Planta* and *In Vitro* conditions.

41

42 Introduction

43 To investigate a set of target genes expression during a set of target conditions there is a need for
44 RT-qPCR reference genes (housekeeping genes) that are stably expressed under all investigated
45 target conditions (Czechowski, 2005; Eisenberg & Levanon, 2013; Stanton et al., 2017; Carmona
46 et al., 2017; Gao et al., 2018). Traditional reference genes selected before the genomic era has
47 been shown to be far from stable under many conditions, and choosing them can obscure the
48 results (Eisenberg & Levanon, 2013; Stanton et al., 2017). Methods for selecting good reference
49 genes have been devised although these often relies on qPCR data which produces a recursive
50 problem since the same method is used to evaluate if the reference genes are working well as
51 references (Carmona et al., 2017). An alternative strategy using publicly deposited RNAseq data
52 in SRA datafiles have been devised (Carmona et al., 2017) to select stably expressed reference
53 genes under different conditions. In a relative recent study aiming to find stable and reliable
54 reference genes for *Fusarium graminearum* (a model organism in plant pathology) under *In*
55 *Vitro* conditions it was found that *GzUBH* (FGSG_01231) and *EFIA* (FGSG_08811) showed the
56 best performance (Kim & Yun, 2011).

57 As far as we know a similar analysis has not been done for *Fusarium graminearum* for *In*
58 *Planta* conditions and is thus the purpose of this study. It is also of interest to select
59 housekeeping genes with a set of different relative expression so as to match these with the
60 expression of the target genes under target conditions. Affymetrix chips for transcriptomic
61 analysis were made for *F. graminearum* relatively early and many experiments by different labs
62 were carried out with the same chip (FusariumPLEX
63 http://www.plexdb.org/modules/PD_general/pathogens_list.php). This data is publicly available
64 and is thus an alternative to RNAseq data for this fungus for evaluating stable expressed
65 reference genes for *In Vitro* and *In Planta* conditions.

66

67 Materials & Methods

68

69 Transcriptome data download and preparation

70 Transcriptome data for *Fusarium graminearum* (*Gibberella zeae*
71 (Schwein.) Petch), strain Ph1 was downloaded from PLEX DB. We used the datasets
72 FusariumPLEX (http://www.plexdb.org/modules/PD_general/pathogens_list.php). The probe
73 id:s were translated to gene ID following the BROAD protein annotation
74 (*fusarium_graminearum_ph-1_3_proteins.fasta.gz* downloaded from <ftp.broadinstitute.org>, path:
75 */distribution/annotation/fungi/fusarium/genomes/fusarium_graminearum_ph-1*). The translation
76 of the probe-set to the BROAD database FGSG-codes is found in the Supplemental Data S1
77 The chip experiment data (Supplemental Table S1 Showing a listing experiments) were split in
78 two sets, *In Planta* related data and *In Vitro* related data and two Excel sheet matrixes with the

79 different transcriptome expression data were produced, *In Planta* expression (Supplemental Data
80 S2) and *In Vitro* expression (Supplemental Data S3).

81

82 **Finding genes with the least varying gene expression in the two datasets and handling of** 83 **the results.**

84 A simple method was used to find genes with least variation of relative expression in the two
85 datasets. Since gene expression of a particular gene can be normally distributed or have many
86 other distributions, we chose to look for genes with least relative difference between maximum
87 and minimum expression. Thus, we calculated for the set of treatments maximum expression
88 minus minimum gene expression divided by average gene expression $((\text{Max}-\text{Min})/\text{Average})$ and
89 ranked the genes with the lowest values as the least varying genes. Plots illustrating the results
90 were prepared in Excel or in the statistics freeware PAST (<https://folk.uio.no/ohammer/past/>).

91

92 **Results**

93

94 The transcriptomic responses of genes were evaluated for the *In Planta* and *In Vitro* datasets
95 (Supplemental Data S2 and S3). The *In Planta* datasets contains 64 full transcriptome datasets
96 and the *In Vitro* contains 98 datasets from different experiments. We used a simple method for
97 detecting which genes showed least relative difference between maximum and minimum
98 expression in respective datasets (see methods). We then ranked the genes for their suitability as
99 reference genes for qPCR and compared the values for the found genes with the values found for
100 commonly used reference genes for *F. graminearum*, *gamma-actin* (FGSG_07335)(Brown et al.,
101 2011), *GAPDH* (FGSG_06257)(Kim & Yun, 2011; Harris et al., 2016), *EF1A*
102 (FGSG_08811)(Kim & Yun, 2011; Harris et al., 2016) and *B-Tubulin* (FGSG_09530)(Kim &
103 Yun, 2011; Harris et al., 2016). We plotted the average expression level versus relative
104 difference between maximum and minimum expression for all genes for both the *In Planta* and
105 the *In Vitro* data (Supplemental Figures 1 and 2 and Supplemental Data S2 and S3). To highlight
106 the genes of most interest Fig. 1 show the average expression level versus relative difference
107 between maximum and minimum expression for the least varying genes at different levels of
108 average expression for the *In Planta* experiments. A similar plot for the *In Vitro* experiments is
109 shown in Fig. 2. In both plots we have inserted or marked commonly used reference genes. The 4
110 common reference genes performed well for the *In Vitro* dataset (Fig. 2) but were not very good
111 as reference genes for *In Planta* conditions (Fig. 1). To find genes that performed relatively well
112 as housekeeping genes under both *In Planta* and *In Vitro* conditions we ranked the genes for
113 their suitability as reference genes under the two conditions and plotted the found ranks for the
114 genes (Fig. 3). As can be seen in Fig. 3 only five genes were performing well as reference genes
115 under both *In Planta* and *In Vitro* conditions. To further illustrate the difference between *In*
116 *Planta* and *In Vitro* conditions we investigated how much overlap it was among the 100 top
117 ranked genes under both conditions and found that only 20 genes were found on both lists (Fig. 4
118 and Supplemental Table S2). Table 1 lists the 10 best reference genes for each condition as well

119 as their rank under the other condition and a list of the 5 genes that performed well under both
120 conditions (See also Figure 3). Table 1 also shows that the genes with least varying gene
121 expression for the *In Planta* conditions were more likely to perform well also under the *In Vitro*
122 conditions than the reverse, and most interestingly *EF1A* (FGSG_08811) that varied least in
123 expression in the *In Vitro* dataset did not perform well *In Planta*.

124

125 Discussion

126 As often found, the transcription of genes involved in transcription, translation, and protein
127 quality control are often among the ones that are most stably related to general transcription level
128 and thus perform well as reference genes (Eisenberg & Levanon, 2013; Carmona et al., 2017;
129 Gao et al., 2018). The two reference genes previously found to be most reliable for *F.*
130 *graminearum* *In Vitro* conditions (Kim & Yun, 2011) also performed very well in our *In Vitro*
131 dataset, thus giving support to our approach. In our *In Vitro* datasets and *EF1A* was also a top
132 performing reference gene with little variation between treatments.

133

134

135 However, *EF1A* was not a top performing gene under *In Planta* conditions (Table 1) illustrating
136 that although many conditions were used in the *In Vitro* dataset, *In Vitro* growth only shows a
137 limited repertoire of gene expression variation. Interestingly, we found that genes performing
138 well as reference genes under *In Planta* conditions more frequently performed well also under *In*
139 *Vitro* conditions than the reverse. This could indicate that *In Vitro* conditions are more likely to
140 expose only a limited repertoire of gene expression regulations. Thus, *In Vivo* the pathogen
141 appears to display more variable gene expression for most genes than *In Vitro* (see conceptual
142 model in Fig. 5) and that most *In Vitro* patterns of expression are found also *In Vivo*.

143

144 Conclusions

145 Our results can be summarized in the following conclusions concerning selection of reference
146 genes for *F. graminearum* RT-qPCR-studies.

147 i. Use published transcriptome data to find reference genes if this data is available for the
148 target conditions and use simple techniques similar to what is used here or techniques for more
149 advanced and automatic analysis (Carmona et al., 2017).

150 ii. If no published suitable transcriptome data is available for your conditions of interest,
151 generate such data and analyze it as in (i).

152 iii. If no published data is available for the conditions of interest and b. is not possible due to
153 time and money constraints, choose at least two reference genes from the five that are here shown
154 to perform well both *In Planta* and *In Vitro*. Then choose genes involved in different processes.
155 Hopefully, analysis of gene expression of target genes in relation to both these reference genes
156 will give similar conclusions.

157

158 Acknowledgements

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160 Program of Fujian Province.

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164

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191 **Figure legends**

192

193 Figure 1. Plot showing genes with low relative difference between maximum and minimum
194 expression for different average expression levels in the *In Planta* dataset. Red dots indicate the
195 four standard reference genes (Table 1). X-axis=Log2 for average expression of each gene for
196 the *In Planta* data. Y-axis= Log scale for Log2 variation values as Log2 maximum relative
197 difference in expression times 100.

198

199 Figure 2. Plot showing genes with low relative difference between maximum and minimum
200 expression for different average expression levels in the *In Vitro* dataset. Red dots indicate the
201 four standard reference genes (Table 1). X-axis=Log2 for average expression of each gene for
202 the *In Vitro* data. Y-axis= Log scale for Log2 variation values as Log2 maximum relative
203 difference in expression times 100

204

205 Figure 3. Plot showing rank for the relative difference between maximum and minimum
206 expression for the best performing reference genes in the *In Planta* dataset versus the rank in
207 the *In Vitro* dataset. The 5 genes in the lower left corner are the genes that performs best in
208 both datasets (see also Table1).

209

210 Figure 4. Illustrates how much overlap (red) it is among the 100 best reference genes in the *In*
211 *Planta* (green) dataset and The *In Vitro* dataset (blue).

212

213 Figure 5. Thought model of number of conditions *F. graminearum* can grow under in relation to
214 the two datasets. Black= Number of conditions *F. graminearum* can grow under. Green=
215 Number of conditions *F. graminearum* is exposed to in the *In Planta* dataset. Red=Number of
216 conditions *F. graminearum* is exposed to in the *In Vitro* dataset.

217

Table 1 (on next page)

Genes with least varying gene expression for 3 different set of conditions. *In Planta*, *In Vitro*, *In Planta AND In Vitro*.

1 Table 1. Genes with least varying gene expression for 3 different set of conditions. *In Planta*, *In*
 2 *Vitro*, *In Planta* AND *In Vitro*

3

Id	Rank <i>in Vitro</i>	Rank <i>in Planta</i>	Annotation
FGSG_08811	1	207	elongation factor-1
FGSG_04289	2	5	probable histone H4
FGSG_10733	3	16	probable ribosomal protein S28
FGSG_11627	4	629	probable HTA2 - histone H2A.2
FGSG_08743	5	89	conserved hypothetical protein
FGSG_02523	6	4804	probable IgE-dependent histamine-releasing factor
FGSG_01425	7	2530	probable H ⁺ -transporting ATPase
FGSG_10089	8	1026	related to sporulation-specific gene SPS2
FGSG_01504	9	913	probable ribosomal protein L31.e.A cytosolic
FGSG_10235	10	4650	related to rasp f 7 allergen
	Rank <i>in Planta</i>	Rank <i>in Vitro</i>	
FGSG_09733	1	19	related to 20S proteasome maturation factor
FGSG_00656	2	62	related to F1F0-ATP synthase subunit G
FGSG_06921	3	23	probable RPL39 - 60S large subunit ribosomal protein L39.e
FGSG_10001	4	214	probable 13 kD U4/U6.U5 snRNP associate protein Snu13
FGSG_04289	5	2	probable histone H4
FGSG_02461	6	142	probable MDH1 - malate dehydrogenase precursor mitochondrial
FGSG_09667	7	17	ubiquinol cytochrome c reductase 8.5 kDa subunit
FGSG_09545	8	75	conserved hypothetical protein
FGSG_01897	9	1793	related to microsomal glutathione S-transferase 3
FGSG_06021	10	13	ADP/ATP carrier
Top 5 among top 20 found within top 100 of both <i>in Planta</i> and <i>in Vitro</i>			
	Rank	Rank <i>in Vitro</i> × rank <i>in Planta</i>	
FGSG_04289	1	10	probable histone H4
FGSG_09733	2	19	related to 20S proteasome maturation factor
FGSG_10733	3	48	probable ribosomal protein S28
FGSG_06921	4	69	probable RPL39 - 60S large subunit ribosomal protein L39.e
FGSG_06021	5	130	ADP/ATP carrier

4

5

Figure 1(on next page)

Plot showing genes with low relative difference between maximum and minimum expression for different average expression levels in the *In Planta* dataset.

Red dots indicate the four standard reference genes (Table 1). X-axis= Log_2 for Average expression of each gene for the *In Planta* data. Y-axis= Log scale for Log_2 variation values as Log_2 maximum relative difference in expression times 100.

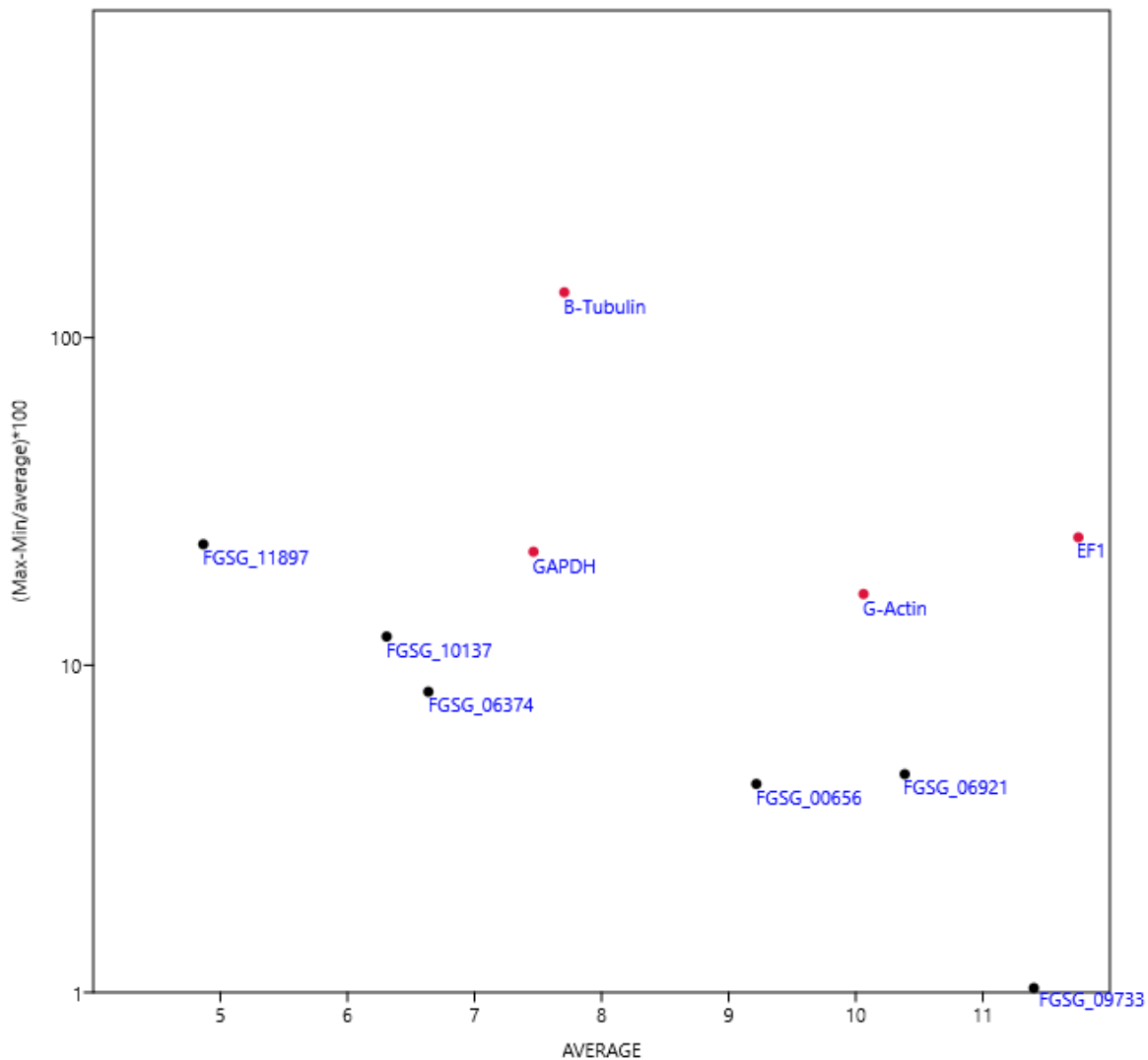


Figure 1. Plot showing genes with low relative difference between maximum and minimum expression for different average expression levels in the *In Planta* dataset. Red dots indicate the four standard reference genes (Table 1). X-axis=Log₂ for Average expression of each gene for the *In Planta* data. Y-axis= Log scale for Log₂ variation values as Log₂ maximum relative difference in expression times 100

Figure 2(on next page)

Plot showing genes with low relative difference between maximum and minimum expression for different average expression levels in the *In Vitro* dataset.

Red dots indicate the four standard reference genes (Table 1). X-axis= Log_2 for Average expression of each gene for the *In Vitro* data. Y-axis= Log scale for Log_2 variation values as Log_2 maximum relative difference in expression times 100.

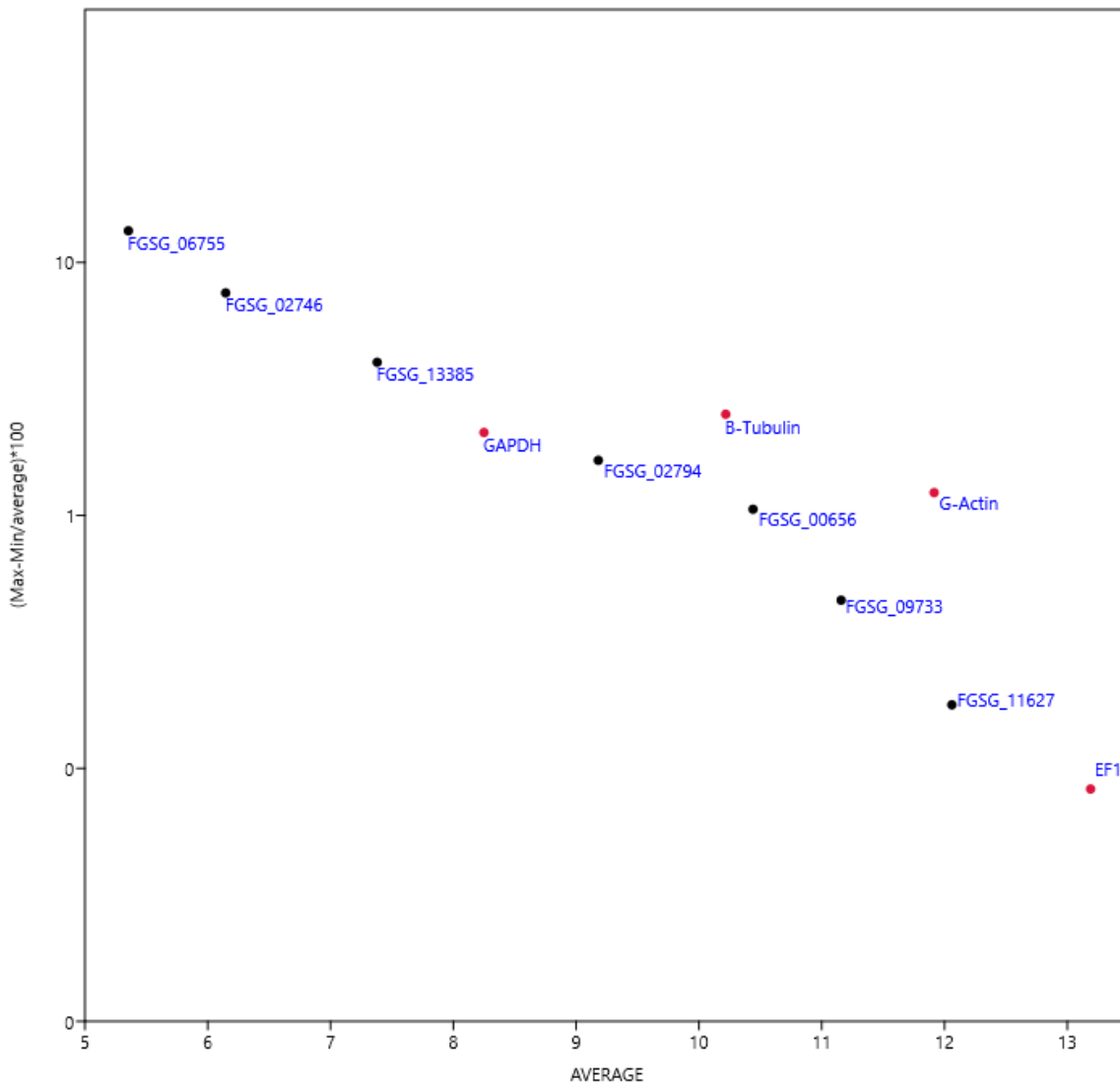


Figure 2. Plot showing genes with low relative difference between maximum and minimum expression for different average expression levels in the *In Vitro* dataset. Red dots indicate the four standard reference genes (Table 1). X-axis=Log2 for Average expression of each gene for the *In Vitro* data. Y-axis= Log scale for Log2 variation values as Log2 maximum relative difference in expression times 100

Figure 3(on next page)

Plot showing rank for the relative difference between maximum and minimum expression for the best performing reference genes in the *In Planta* dataset versus the rank in the *In Vitro* dataset.

The 5 genes in the lower left corner are the genes that performs best in both datasets (see also Table1).

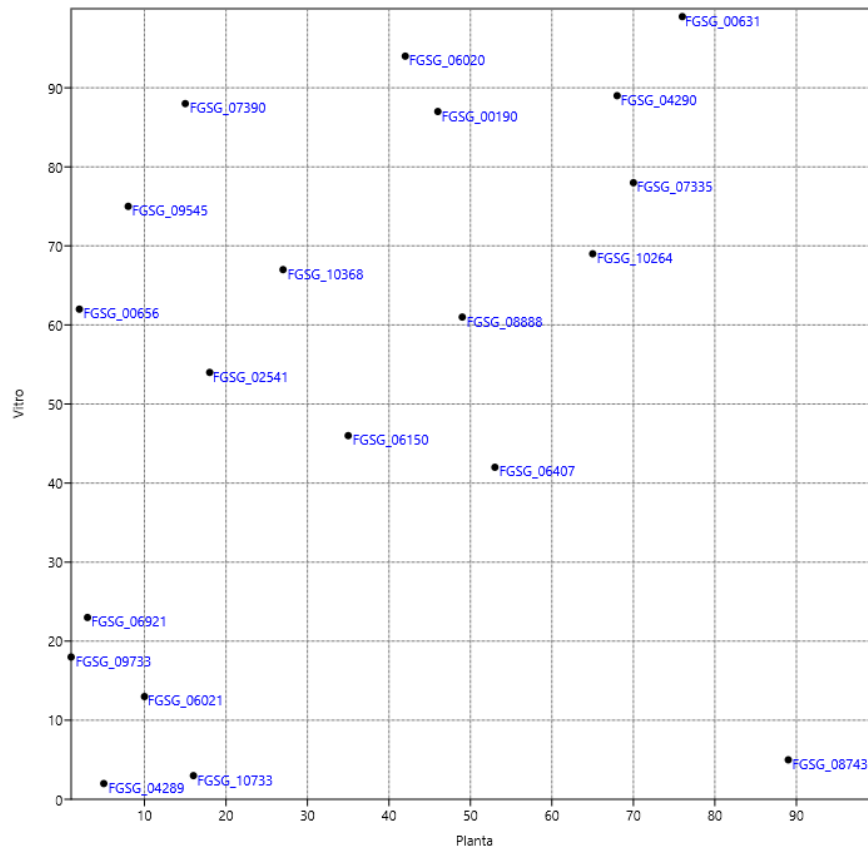


Figure 3. Plot showing rank for the relative difference between maximum and minimum expression for the best performing reference genes in the *In Planta* dataset versus the rank in the *In Vitro* dataset. The 5 genes in the lower left corner are the genes that performs best in both datasets (see also Table1).

Figure 4(on next page)

Illustrates how much overlap (red) it is among the 100 best reference genes in the *In Planta* (green) dataset and The *In Vitro* dataset (blue).

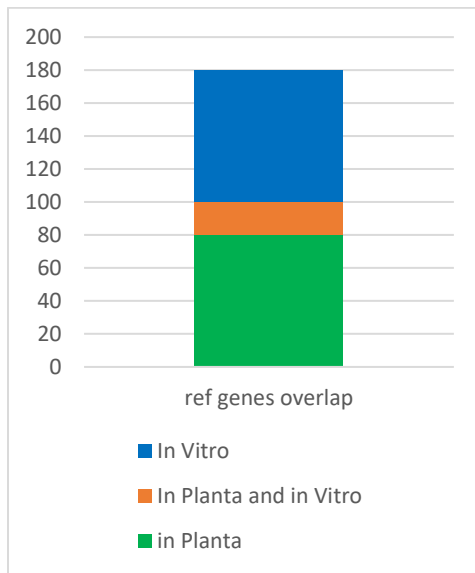


Figure 4. Illustrates how much overlap (red) it is among the 100 best reference genes in the *In Planta* (green) dataset and The *In Vitro* dataset (blue).

Figure 5(on next page)

Thought model of number of conditions *F. graminearum* can grow under in relation to the two datasets.

Black= Number of conditions *F. graminearum* can grow under. Green= Number of conditions *F. graminearum* is exposed to in the *In Planta* dataset. Red=Number of conditions *F. graminearum* is exposed to in the *In Vitro* dataset.

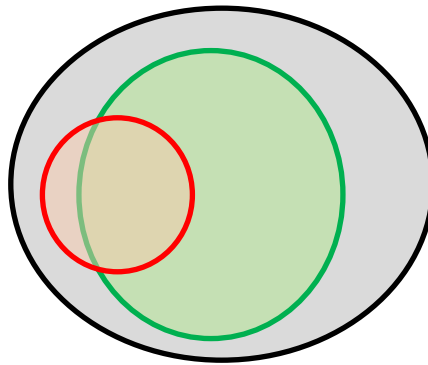


Figure 5. Thought model of number of conditions *F. graminearum* can grow under in relation to the two datasets. Black= Number of conditions *F. graminearum* can grow under. Green= Number of conditions *F. graminearum* is exposed to in the *In Planta* dataset. Red=Number of conditions *F. graminearum* is exposed to in the *In Vitro* dataset.