APPLICATION OF AN OPTIMIZED ANNOTATION PIPELINE TO THE *CRYPTOCOCCUS DEUTEROGATTII* GENOME REVEALS DYNAMIC PRIMARY METABOLIC GENE CLUSTERS AND GENOMIC IMPACT OF RNAI LOSS

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Abstract

Evaluating the quality of a *de novo* annotation of a complex fungal genome based on RNA-seq data remains a challenge. In this study, we sequentially optimized a Cufflinks-CodingQuary based bioinformatics pipeline fed with RNA-seq data using the manually annotated model pathogenic yeasts *Cryptococcus neoformans* and *Cryptococcus deneoformans* as test cases. Our results demonstrate that the quality of the annotation is sensitive to the quantity of RNA-seq data used and that the best quality is obtained with 5 to 10 million reads per RNA-seq replicate. We also demonstrated that the number of introns predicted is an excellent *a priori* indicator of the quality of the final *de novo* annotation. We then used this pipeline to annotate the genome of the RNAi-deficient species *Cryptococcus deuterogattii* strain R265 using RNA-seq data. Dynamic transcriptome analysis revealed that intron retention is more prominent in *C. deuterogattii* than in the other RNAi-proficient species *C. neoformans* and *C. deneoformans*. In contrast, the average level of antisense transcription was not higher in *C. deuterogattii*. Comparative gene content analysis identified 21 clusters enriched in transcription factors and transporters that have been lost. Interestingly, analysis of the subtelomeric regions in these three annotated species identified a similar gene enrichment, reminiscent of the structure of primary metabolic clusters. Our data suggest that there is active exchange between subtelomeric regions, and that other chromosomal regions might participate in adaptive diversification of *Cryptococcus* metabolite assimilation potential.

61 **Introduction**

62 In recent years, we have seen an astonishing multiplication of fungal genome sequences
63 (JAMES *et al.* 2020). Long-read sequencing and adapted bioinformatics tools are quickly improving
64 as well. It is expected that telomere-to-telomere whole-genome sequencing will soon become
65 standard for reference genomes of diverse organisms (GIORDANO *et al.* 2017; DAL MOLIN *et al.* 2018;
66 YADAV *et al.* 2018). Yet, fungal genomes remain difficult to annotate. Historically, most annotation
67 tools have relied upon comparative genomics, but other pipelines utilize RNA-seq data or a
68 combination of both approaches to propose gene annotation models (CANTAREL *et al.* 2008; HAAS *et*
69 *al.* 2011; MIN *et al.* 2017; HARIDAS *et al.* 2018). These pipelines are very efficient in intron-poor
70 species, at least for predicting coding regions. For instance, a recent MAKER-based optimized
71 pipeline tested on 39 budding yeast genomes missed only 3.9% of genes and 4.8% of exons, on
72 average (SHEN *et al.* 2018). However, the results were poorer in intron-rich species, for which gene
73 annotation is challenging. Even when RNA-seq data are available, it is still very difficult to correctly
74 predict the exon-intron structure primarily because fungal exons can be can extremely short
75 (JANBON *et al.* 2014), but also because these genomes are compact. Thus, when tested on fungal
76 data sets, *de novo* transcriptome assemblers like Trinity (GRABHERR *et al.* 2011) or Cufflinks
77 (TRAPNELL *et al.* 2010) tend to predict very large transcripts with no biological relevance.
78 Nevertheless, several pipelines have been published and sequencing centers like the Joint Genome
79 Institute (JGI) and the Broad Institute have developed specialized pipelines to produce annotation
80 drafts, which are very useful in large-scale comparison analyses (HAAS *et al.* 2011; HARIDAS *et al.*
81 2018).

82 Some methods, like the construction of large deletion collections, or precise analysis of
83 gene content needs more precise annotation, and the annotation strategy applied will depend on
84 the goal of the research (MUDGE AND HARROW 2016). Manual curation of a pre-annotated genome
85 will likely result in the highest-quality gene prediction. Some tools, like Artemis (CARVER *et al.* 2012)

86 and Apollo (DUNN *et al.* 2019), have been used to manually curate annotation, but they are time
87 consuming even when several annotators are implemented. Without manual curation, it is
88 impossible to anticipate the results from an annotation bioinformatics pipeline fed with RNA-seq
89 data. Typically, the quality of the prediction will depend on the diversity, quantity, and quality of
90 the data, but no *a priori* indicator exists to determine if the *de novo* gene prediction is accurate.

91 Pathogenic *Cryptococcus* species are basidiomycete yeasts, which cause nearly 200,000
92 deaths annually around the world (KWON-CHUNG *et al.* 2014). There are currently eight recognized
93 pathogenic species of *Cryptococcus* (HAGEN *et al.* 2015; Farrer et al., 2019). Manual annotation of
94 the *Cryptococcus neoformans* and *Cryptococcus deneoformans* reference genomes revealed
95 complex and dynamic transcriptomes (JANBON *et al.* 2014; WALLACE *et al.* 2020). These annotations
96 were recently completed through precise identification of the transcript leader (TL) and 3'UTR
97 sequences through TSS-seq and 3UTR-seq analyses; these annotations are likely the most
98 complete and detailed annotations in intron-rich fungi (WALLACE *et al.* 2020). With 99.5% of 6,795
99 annotated coding genes containing introns, five to six introns per coding gene, and 37,832 introns
100 in total, an automatic annotation of these genomes would be considered highly challenging even
101 with the large sets of RNA-seq data that have been produced (WILM *et al.* 2007; JANBON 2018;
102 WALLACE *et al.* 2020).

103 In this study, we compared the performances of three annotation pipelines fed with RNA-
104 seq data. We gradually optimized the quality of the *de novo* annotation using the well-annotated
105 genomes of *C. neoformans* and *C. deneoformans* as ground-truth inputs. We found that the
106 quantity of data used should not be too large and that the number of introns predicted had a
107 positive, linear relationship with the quality of the *de novo* annotation. We used this pipeline to re-
108 annotate the reference genome of the RNAi-deficient *Cryptococcus deuterogattii* strain R265 using
109 RNA-seq data. Analysis of the transcriptome dynamics of these three *Cryptococcus* species

110 revealed that although the sense/antisense transcript ratio is similar across all three species,
111 intron retention is higher in *C. deuterogattii*. Comparative gene content analysis identified a list of
112 genes that are absent or largely truncated in R265, many of which have been implicated in RNAi-
113 mediated silencing in *Cryptococcus* species. Finally, we also identified several primary metabolic
114 gene clusters (MGCs) that are absent in R265 and associated this loss with the subtelomeric gene
115 content. Our data suggest an active exchange of MGCs between subtelomeric regions and more
116 central regions of the genome. This exchange might contribute to the adaptive diversification of
117 metabolite assimilation potential in *Cryptococcus*.

118

119 **MATERIALS AND METHODS**

120

121 **RNA-Seq sample and data production**

122 RNA-seq libraries from four growth conditions (exponential phase at 30°C, + exponential phase at
123 37°C, stationary phase at 30°C, and stationary phase at 37°), conducted in triplicate, of *C.*
124 *neoformans* H99 and *C. deneoformans* JEC21 used in this study have been previously described
125 (WALLACE et al. 2020). The *C. deuterogattii* R265 strain was grown in YPD at 30°C and 37°C under
126 agitation to exponential or early stationary phase as previously described (WALLACE et al. 2020).
127 Briefly, early stationary phase was obtained after 18 h of growth (final OD 600 = 15) starting from
128 at OD600 = 0.5. Each *Cryptococcus* cell preparation was spiked in with one tenth (OD/OD) of *S.*
129 *cerevisiae* strain FY834 cells grown in YPD at 30°C in stationary phase. Cells were washed, snap
130 frozen and used to prepare RNA and total DNA samples. Biological triplicates were prepared in each
131 condition. For RNA-seq, strand-specific, paired-end cDNA libraries were prepared from 10 µg of total
132 RNA following poly-A purification using the TruSeq Stranded mRNA kit (Illumina) according to
133 manufacturer's instructions. cDNA fragments of ~400 bp were purified from each library and

134 confirmed for quality by Bioanalyzer (Agilent). DNA-Seq libraries were prepared using the kit TruSeq
135 DNA PCR-Free (Illumina). Then, 100 bases were sequenced from both ends using an Illumina
136 HiSeq2500 instrument according to the manufacturer's instructions (Illumina). For the mating
137 condition, total RNA was isolated (in biological triplicates) from a *C. neoformans* cross between the
138 congenic mating partners H99 (*MAT*α) and YL99 (*MAT***a**) (SEMIGHINI et al., 2011) or a *C. deuterogattii*
139 cross between the congenic mating partners R265 (*MAT*α) and AIR265 (*MAT***a**) (ZHU et al. 2013).
140 Briefly, overnight cultures were grown under standard laboratory conditions in YPD at 30°C.
141 Overnight cultures were diluted to an OD600 = 1.0, and cells from both strains were mixed, spotted
142 onto V8 (pH = 5) mating medium, and incubated in the dark at room temperature for 48 h. Cells
143 were scraped from mating plates, snap frozen, and RNA was isolated using Trizol following the
144 manufacturer's protocol. RNA quality was confirmed by Bioanalyzer (Agilent) and RNA samples were
145 depleted of ribosomal RNA with the Ribo-Zero Gold rRNA Removal Kit for Yeast (Illumina). Strand-
146 specific, paired-end cDNA libraries were prepared using the TruSeq Stranded mRNA kit (Illumina),
147 and 150 bases were sequenced from both ends using an Illumina HiSeq4000 instrument according
148 to the manufacturer's instructions (Illumina).

149 **RNA-Seq library trimming and rRNA cleaning**

150 The paired reads from the RNA-seq libraries were trimmed for low quality reads and Illumina TruSeq
151 adapters were removed with Cutadapt v1.9.1 (MARTIN 2011) with the following parameters: --trim-
152 qualities 30 –e (maximum error rate) 0.1 --times 3 --overlap 6 --minimum-length 30. The cleaning of
153 rRNA sequences was performed with Bowtie2 v2.3.3 (LANGMEAD AND SALZBERG 2012) with default
154 parameters; unmapped paired reads were reported using option --un-conc to identify reads that did
155 not align with rRNA sequences.

156 **RNA-Seq library mapping**

157 The cleaned reads from RNA-seq paired-end libraries from *C. neoformans* H99, *C. deneoformans*
158 JEC21, and *C. deuterogattii* R265 were mapped against their reference genomes (NCBI Genome
159 Assemblies GCA_000149245.3, GCA_000091045.1 and GCA_002954075.1) with Tophat2 v2.0.14
160 (KIM *et al.* 2013) and the following parameters: minimum intron length 30; minimum intron
161 coverage 30; minimum intron segment 30; maximum intron length 4000; maximum multihits 1;
162 microexon search; and library-type fr-firststrand or fr-secondstrand (according to the RNA-seq
163 library).

164 **Pipeline selection**

165 The RNA-seq mapped reads from *C. neoformans* H99 and *C. deneoformans* JEC21 from the EXPO30
166 condition (exponential growth at 30 C) were tested in the three pipelines for gene prediction.
167 BRAKER1 (HOFF *et al.* 2016) was performed with the default parameters plus the exclusion of
168 alternative transcripts (--alternatives-from-evidence=false) using the three replicates (A, B, and C)
169 as RNA-seq source. Cuff-CQ (Cufflinks v2.1.1 ((TRAPNELL *et al.* 2010)) /Coding Quarry v2.0 (TESTA *et al.*
170 2015)) and C3Q (Cufflinks v2.1.1/Cuffmerge/Coding Quarry v2.0) were tested with the basic
171 parameters: minimum intron length (30); maximum intron length (4000); minimum isoform fraction
172 (0.9); and overlap radius (10). The merged BAM file generated by the three replicates (A, B, and C)
173 and used in the Cuff-CQ pipeline was obtained with Samtools *merge.* C3Q was performed separately
174 for the three BAM files; the GTF files generated by the three predictions (for replicates A, B, and C)
175 were then combined by Cuffmerge and the resulting transcripts were processed by CodingQuarry.
176 The evaluation of the pipeline sensitivity and precision for gene prediction was performed by
177 comparing the predicted annotations against the H99 and JEC21 reference annotations (WALLACE
178 et al., 2020) with the GFFCompare program (PERTEA AND PERTEA 2020).

179 *For a better understanding, the C3Q pipeline with the basic Cufflinks parameters is named as C3Q1*
180 *protocol in the results section.*

181 **Cufflinks parameters selection**

182 The selection of the best Cufflinks parameter combination was also performed with EXPO30 RNA-
183 seq libraries from *C. neoformans* H99 and *C. deneoformans* JEC21 according to the C3Q pipeline. For
184 this, the Cufflinks transcript assembly generated for each EXPO30 replicate (A, B, and C) was tested
185 with fixed and variable parameter combinations (Table 1). Subsequently, as established for the C3Q
186 pipeline, the predicted GTFs were merged and processed by CodingQuarry. All combinations include
187 minimum intron length 30; maximum intron length 4000; and minimum isoform fraction 0.9; since
188 we want to remove all isoforms. The variable parameters include: pre-mRNA fraction 0.15 to 1.0;
189 small anchor fraction 0.0; minimum fragments per transfag 1; overlap radius 1, 10 and 100; 3'
190 trimming (--trim-3-avgcov-thresh and –trim-3-dropoff-frac) 0. The evaluation of the Cufflinks
191 parameters for sensitivity and specificity for gene prediction was performed by comparison of the
192 predicted annotations against the H99 and JEC21 reference annotations with the GFFCompare
193 program.

194 *For a better understanding, the C3Q pipeline with the "Q" Cufflinks parameters (selected*
195 *combination) is named as C3Q2 protocol in the results section.*

196

197 **Table 1.**

	Cufflinks parameter combinations
A	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9
B	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --min-frags-per-transfag 1
C	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --pre-mrna-fraction 0.25
D	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --overlap-radius 10
E	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --overlap-radius 100
F	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --trim-3-avgcov-thres 0 --trim-3-dropoff-frac 0.0
G	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --pre-mrna-fraction 0.25 --overlap-radius 10 --trim-3-avgcov-thresh 0 --trim-3-dropoff-frac 0.0
H	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --pre-mrna-fraction 0.25 --overlap-radius 10 --trim-3-avgcov-thresh 0 --trim-3-dropoff-frac 0.0 --min-frags-per-transfag 1
I	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --pre-mrna-fraction 0.25 --overlap-radius 1 --trim-3-avgcov-thresh 0 --trim-3-dropoff-frac 0.0
J	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --pre-mrna-fraction 0.25 --overlap-radius 10 --trim-3-avgcov-thresh 0 --trim-3-dropoff-frac 0.0 --min-frags-per-transfag 1
K	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --pre-mrna-fraction 0.25 --overlap-radius 1 --trim-3-avgcov-thresh 0 --trim-3-dropoff-frac 0.0 --small-anchor-fraction 0.0
L	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --pre-mrna-fraction 0.50 --overlap-radius 1 --trim-3-avgcov-thresh 0 --trim-3-dropoff-frac 0.0 --small-anchor-fraction 0.0
M	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --pre-mrna-fraction 0.75 --overlap-radius 1 --trim-3-avgcov-thresh 0 --trim-3-dropoff-frac 0.0 --small-anchor-fraction 0.0
N	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --pre-mrna-fraction 0.80 --overlap-radius 1 --trim-3-avgcov-thresh 0 --trim-3-dropoff-frac 0.0 --small-anchor-fraction 0.0
O	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --pre-mrna-fraction 0.90 --overlap-radius 1 --trim-3-avgcov-thresh 0 --trim-3-dropoff-frac 0.0 --small-anchor-fraction 0.0

P	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --pre-mrna-fraction 1.0 --overlap-radius 1 --trim-3-avgcov-thresh 0 --trim-3-dropoff-frac 0.0 --small-anchor-fraction 0.0
Q	--max-intron-length 4000 --min-intron-length 30 --min-isoform-fraction 0.9 --pre-mrna-fraction 0.85 --overlap-radius 1 --trim-3-avgcov-thresh 0 --trim-3-dropoff-frac 0.0 --small-anchor-fraction 0.0

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199

200

201 **Gene predictions with H99 and JEC21 RNA-seq libraries**

202 The validation of this gene prediction system was evaluated by applying the C3Q pipeline with the
203 best selected Cufflinks parameters ("Q" combination) to all RNA-seq libraries from *C. neoformans*
204 H99 and *C. deneoformans* JEC21. For H99, the fifteen libraries obtained from the five growth
205 conditions were used (Exponential phase at 30°C, Exponential phase at 37°C; Stationary phase at
206 30°C, Stationary phase at 37°C and Mating). For JEC21, we tested twelve libraries obtained from
207 four growth conditions (Exponential phase at 30°C, Exponential phase at 37°C; Stationary phase at
208 30°C and Stationary phase at 37°C).

209 The evaluation of the sensitivity and specificity for gene prediction was performed by comparison
210 of the predicted annotations against H99 and JEC21 reference annotations with the GFFCompare
211 program.

212 *For a better understanding, the C3Q pipeline with the "Q" Cufflinks parameters and the RNA-seq*
213 *libraries for all the sequenced conditions ("ES3037M" for C. neoformans H99 and "ES3037" for C.*
214 *deneoformans JEC21) is named as C3Q3 protocol in the results section.*

215 *ES3037M: Exponential phase at 30°C (EXPO30) + Exponential phase at 37°C (EXPO30) + Stationary
216 phase at 30°C (STAT30) + Stationary phase at 37°C (STAT37) + Mating

217 *ES3037: Exponential phase at 30°C (EXPO30) + Exponential phase at 37°C (EXPO30) + Stationary
218 phase at 30°C (STAT30) + Stationary phase at 37°C (STAT37)

219 **Effect of different conditions on predictions**

220 To evaluate the effect of the growth conditions on the predicted annotation, we used combinations
221 of RNA-seq libraries derived from two, three, and four of the growth conditions for *C. neoformans*
222 H99 and of two and three of the growth conditions for *C. deneoformans* JEC21. The predictions for
223 each combination were performed according to the C3Q pipeline and "Q" Cufflinks parameters. The
224 evaluation of the sensitivity and specificity for gene prediction was performed by comparison of the
225 predicted annotations against H99 and JEC21 reference annotations with the GFFCompare program.

226 **Evaluation of the effect of the sequencing depth on gene prediction quality**

227 The evaluation of the effect of the sequencing depth on gene prediction was performed by down
228 sampling the three RNA-seq libraries from the EXPO30 condition (replicates A, B, and C) with the
229 tool *PositionBasedDownsampleSam* from Picard package (https://broadinstitute.github.io/picard/).
230 In this analysis, *C. neoformans* H99 and *C. deneoformans* JEC21 were used. According to a random
231 algorithm that downsamples BAM files, we used defined fractions of 1, 5, 7.5, 10, 15, 20, 30 and 40
232 million reads for each replicate. Subsequently, the predictions were performed according to the
233 C3Q pipeline with the Cufflinks "Q" parameter combination using the downsampled files. Evaluation
234 of the sensitivity and specificity of gene prediction was performed by comparison of the predicted
235 annotations against H99 and JEC21 reference annotations with the GFFCompare program.

236 **Gene predictions with downsampled H99 and JEC21 RNA-seq libraries**

237 Gene prediction using the downsampled BAM files from the RNA-seq conditions was performed
238 according the C3Q pipeline with "Q" Cufflinks parameters and the downsampled RNA-Seq alignment
239 files for all *C. neoformans* H99 (Exponential phase at 30°C, Exponential phase at 37°C, Stationary

240 phase at 30°C, Stationary phase at 37°C and Mating) and *C. deneoformans* JEC21 (Exponential phase
241 at 30°C, Exponential phase at 37°C; Stationary phase at 30°C and Stationary phase at 37°C) growth
242 conditions. The downsampling of each replicate to 7.5 million reads was performed with the Picard
243 package, as previously described. Evaluation of the sensitivity and specificity of gene prediction was
244 performed by comparison of the predicted annotations against H99 and JEC21 reference
245 annotations with the GFFCompare program.

246 *For a better understanding, the C3Q pipeline with the "Q" Cufflinks parameters and the subsampled*
247 *BAM files from RNA-seq libraries for all the growth conditions ("ES3037M" for C. neoformans H99*
248 *and "ES3037" for C. deneoformans JEC21) is named as C3Q4 protocol in the results section.*

249 **Characterization of novel and missed loci**

250 The identification of novel and missed loci was performed with the GFFCompare program using the
251 reference annotations from *C. neoformans* H99 and *C. deneoformans* JEC21 and the predicted C3Q
252 gene annotations. Evaluation of the functional annotation (function, presence of domain signatures)
253 of these sequences was performed by Blastp and Interproscan search from Blast2GO (CONESA *et al.*
254 2005). The expression quantification of these sequences was performed with HTSeq-count (ANDERS
255 *et al.* 2014) with the following parameters *--stranded yes -f bam -r pos -t CDS*.

256 **Deletion of dubious novel loci from predictions**

257 Deletion of dubious novel sequences was tested with predicted transcripts of 100 nt, 150 nt, 200 nt
258 and 300 nt, as well as intronless sequences of 300 nt from *C. neoformans* H99 and *C. deneoformans*
259 JEC21 C3Q predictions. The sequence deletion and evaluation of the results was performed with an
260 in-house AWK script and the GFFCompare program. Deletion of genome-predicted sequences
261 without supporting reads and those with low FPKM values were performed and evaluated with an
262 in-house AWK script combined with the HTSeq-count and the GFFCompare program. Deletion of
263 alternative transcripts from multi-transcript loci was also performed with an in-house AWK script

264 and GFFCompare. In this process, we selected for transcripts predicted by Cufflinks with supporting
265 RNA-seq evidence. Of these selected transcripts, the longest transcript was chosen. For the other
266 genes predicted only from genome sequencing (without RNA-seq evidence), the longest transcript
267 was selected.

268 We assessed the sensitivity and specificity of the C3Q predictions for *C. neoformans* H99 and *C.*
269 *deneoformans* JEC21 against their reference annotations to analyze the effect of dubious sequence
270 deletion. Filter combinations with the low numbers of remnant novel transcripts and smaller
271 reduction in the prediction quality parameters were favored.

272 *For a better understanding, the C3Q pipeline with the "Q" Cufflinks parameters, the subsampled*
273 *BAM from RNA-seq libraries for all the sequenced conditions ("ES3037M" for C. neoformans H99 and*
274 *"ES3037" for C. deneoformans JEC21), and the sequence filtering (sequences up to 150 nt, intronless*
275 *sequences up to 300 nt, genome-predicted sequences without reads and alternative transcripts) is*
276 *named as C3Q5 protocol in the results section.*

277 **Retrieval of deleted and non-predicted loci**

278 The mapping of *C. neoformans* H99 protein sequences in the *C. deneoformans* JEC21 genome and
279 JEC21 protein sequences in the H99 genome by Exonerate v2.2.0 program
280 (https://www.ebi.ac.uk/about/vertebrate-genomics/software/exonerate) with the following
281 parameters (*protein2genome --percent 30 -- bestn 1 --minintron 30 – maxintron 4000 --*
282 *showalignment false --showvulgar false --showtargetgff true --refine region --subopt false)* was
283 performed to recover sequences deleted in the previous filtering step with conserved orthology in
284 *Cryptococcus*. For this purpose, the mapped gene coordinates matching previously predicted
285 sequences (GFFCompare program) were used to add these deleted genes to the annotation with an
286 in-house AWK script. The addition of non-predicted genes was performed by comparing the mapped
287 protein sequence coordinates and the genomic regions without predicted genes.

288 *For a better understanding, the C3Q pipeline with the "Q" Cufflinks parameters, the subsampled*
289 *BAM from RNA-Seq libraries for all the sequenced conditions ("ES3037M" for C. neoformans H99 and*
290 *"ES3037" for C. deneoformans JEC21), the sequence filtering (sequences up to 150 nt, intronless*
291 *sequences up to 300 nt, genome-predicted sequences without reads and alternative transcripts), and*
292 *the Exonerate-based retrieval of deleted and non-predicted genes is named as C3Q6 protocol in the*
293 *results section.*

294 **Automatization of the C3Q pipeline**

295 The C3Q pipeline, an automatic gene predictor, was built with Python3 code *(C3Q_gene-*
296 *predictor.py)* and is available in Github ()

297 The C3Q pipeline includes all established parameters for *Cryptococcus* genome annotation (C3Q6
298 protocol):

299 - The Cufflinks assembly of transcripts for each RNA-seq library.

300 - The merging of the generated GTF files by Cuffmerge.

301 - The GTF conversion to GFF format (needed for CodingQuarry).

302 - The training and genome prediction by CodingQuarry, using the merged GFF file and the reference
303 genome.

304 - The sequence filtering: deletion of small transcripts up to 150 nt and intronless transcripts up to
305 300 nt; deletion of genome-predicted sequences without supporting reads and deletion of
306 alternative transcripts from multi-transcript loci.

307 - The retrieval of deleted and non-predicted orthologous/paralogous sequences by Exonerate
308 (modified version with GFF3 support from https://github.com/hotdogee/exonerate-gff3).

309 **Gene prediction in *C. deuterogattii* R265**

310 Gene prediction in *C. deuterogattii* R265 was performed with the C3Q pipeline (C3Q6 protocol) using
311 the *C3Q_gene-predictor.py* script. For this, the five RNA-seq triplicate libraries from *C. deuterogattii*
312 R265 (Exponential phase at 30°C, Exponential phase at 37°C, Stationary phase at 30°C, Stationary
313 phase at 37°C and Mating) were subsampled to 7.5 million reads each, and input into the script in
314 addition to the *C. neoformans* H99 and *C. deneoformans* JEC21 protein sequences for the Exonerate
315 step.

316 Concomitantly, manual correction of genes from chromosomes 9 and 14 was performed with the
317 software Artemis (CARVER et al., 2012), the R265 genome (NCBI assembly GCA_002954075.1), and
318 the stranded paired-end RNA-seq data from *C. deuterogattii* R265 in the five growth conditions.

319 The predicted annotation was evaluated by comparing it to the manually corrected genes from
320 chromosomes 9 and 14, as well as the *C. deuterogattii* R265 annotations from Broad (NCBI assembly
321 GCA_000149475.3) and Ferrareze et al., 2017.

322 CDS gene coordinates from old annotations were also identified in the new sequenced genome with
323 Exonerate aligner (*coding2genome*). The predicted novel genes were named with CNBG ID numbers
324 above 10000. The statistics of the gene annotations ware generated by AGAT script
325 *agat_sp_statistics.pl* (https://github.com/NBISweden/AGAT). The final annotation is available in file
326 S1.

327 **Comparison of orthologue groups across *Cryptococcus* species**

328 Ortho-groups and genes unique to *C. neoformans* H99, *C. deneoformans* JEC21 and *C. deuterogattii*
329 R265 were evaluated with Orthofinder v2.3.3 configured to use the Blast aligner. Gene size
330 comparisons were performed with orthologues and paralogues (if the true orthologue was not
331 known) obtained from the OrthoFinder analysis, as well as gene sizes. For the ratio calculation, the
332 size (nt) of the R265 gene was divided by the size (nt) of the H99 and JEC21 orthologous genes. The

333 analysis of conserved domains in unique sequences and the functional annotation of *C. deuterogattii*
334 R265 were performed with Blast2GO (Blastp, Interproscan and GO mapping).

335 **Gene orientation analysis**

336 To determine the frequency of tandem genes with the same orientation, we searched for groups of
337 two, three, four, or five genes assigned to the same DNA strand in the GFF file from *C. deuterogatti*
338 R265 (with our new annotation), *C. neoformans* H99 (Genome assembly reference
339 GCF_000149245.1), and *C. deneoformans* JEC21 (Genome assembly reference GCF_000091045.1)
340 annotations. This was performed by analyzing the orientation of each gene pair in the GFF file from
341 R265, H99 and JEC21, recording the frequency of genes converging (tail-to-tail), diverging (head-to-
342 head), and in the same orientation (head-to-tail) in the whole genome and for each chromosome.
343 This was executed using an in-house Python script (script *gene_organization_analysis.py*).

344 **Antisense transcription analysis**

345 To evaluate the antisense transcription in the genomes analyzed, we first generated a reversed
346 annotation, which consisted of a GFF file with genes assigned to the opposite strand of their actual
347 annotation. With the annotation and the reverse annotation, we analyzed the percentage of
348 antisense transcription for each protein coding gene using the software HTseq-count using the
349 following attributes *(-f bam -r pos - s yes -t CDS -i ID -m intersection-nonempty --nonunique none*
350 *(.bam) (.gff))* and the distinct RNA-seq libraries. Sense/antisense counts ratios for each gene for each
351 condition were plotted. The script used for generation of a reverse GFF is available (*reverse_gff.py*).

352 **Intron retention evaluation**

353 For a given intron, an IR index was calculated by determining the ratio of spliced:non-spliced reads
354 at the upstream and downstream exon-intron junctions and choosing the lowest of these two
355 numbers. These IR indices were calculated using RNA-seq obtained from cells growing in each of the

356 four growth conditions. An intron was considered to be regulated by intron retention when the IR
357 index was at least 0.01. We restricted our analysis to introns with more than 10 spliced reads.

358 **Statistical analysis**

359 The proportion of genes with intron retention regulation was compared amongst the distinct
360 conditions using one way ANOVA followed by multi-comparison analysis corrected by FDR. The X-
361 squared analysis was conducted using R (version 4.0.2) and plots were prepared using the corrplot
362 package (version 0.84).

363 **Availability and accession number**

364 Raw and summarized sequencing data are available at SRA with the accession number:
365 SAMN15950139. The C3Q pipeline is available in Github (https://github.com/UBTEC/C3Q);
366 Supplemental files available at FigShare. File S1 contain the *Cryptococcus deuterogattii* gff
367 annotation file.

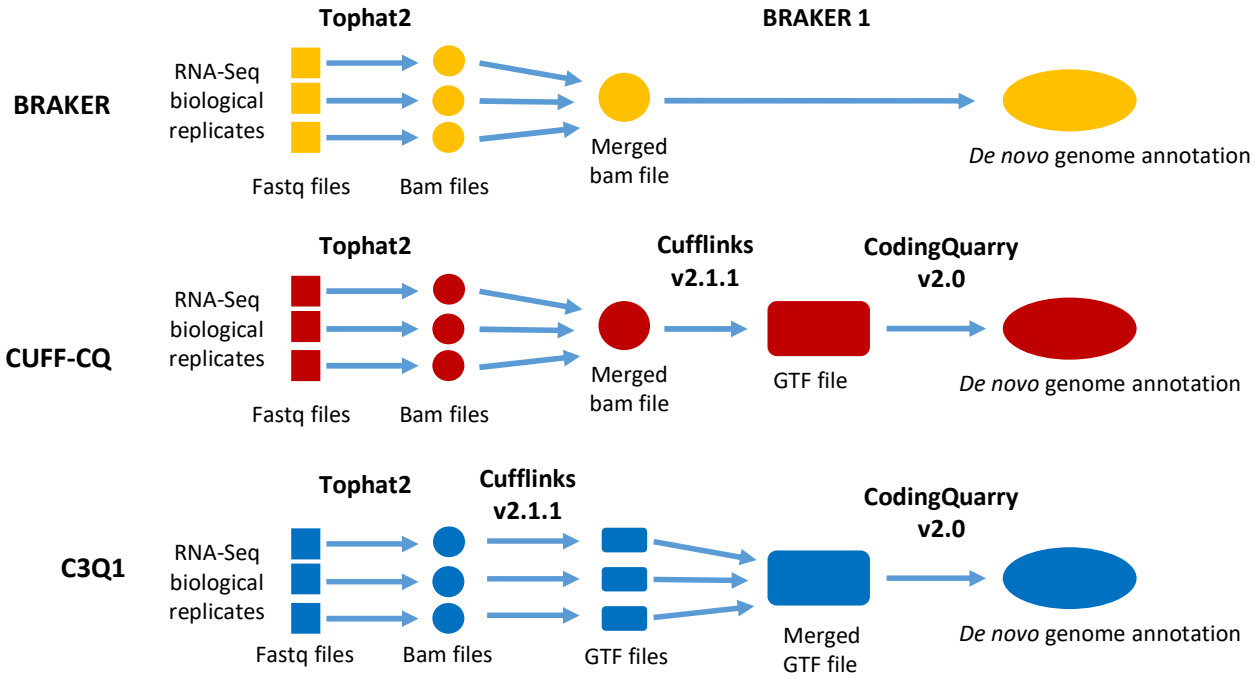
368

369 **RESULTS**

370 **Pipeline selection**

371 We first compared the performance of two previously published annotation pipelines used
372 in coding gene *de novo* annotation in intron-rich fungal genomes using RNA-seq data. The
373 BRAKER1 pipeline, which combines GeneMark-ET (LOMSADZE *et al.* 2014) and Augustus (STANKE *et*
374 *al.* 2008) and is already optimized with the best prediction parameters (HOFF *et al.* 2016), was
375 compared with a genome annotation pipeline composed of Cufflinks v2.1.1 (TRAPNELL *et al.* 2010)
376 and CodingQuarry v2.0 (TESTA *et al.* 2015). We used the *C. neoformans* H99 and *C. deneoformans*
377 JEC21 genomes as controls to assess of the performance of both pipelines (GONZALEZ-HILARION *et al.*
378 2016; WALLACE *et al.* 2020).

379 For this analysis, we used only RNA-seq data obtained in biological triplicate from cells
380 grown to exponential growth phase at 30°C in complete medium (YPD) (EXPO30) (WALLACE *et al.*
381 2020). Previously described BAM files obtained after alignment of trimmed reads to the *C.*
382 *neoformans* H99 genome were input into the BRAKER1 and Cufflink-CodingQuarry pipelines
383 (WALLACE *et al.* 2020). For the Cufflink-CodingQuarry-based analyses, we used two alternative
384 protocols. In the first case, we first merged the BAM files from each of the three replicates (CUFF-
385 CQ protocol). In the second case, each replicate BAM file was used to generate a unique GTF
386 prediction file, these files were then merged using Cuffmerge and used by CodingQuarry as a
387 single transcript source (C3Q1 protocol) (Figure 1).
388



389

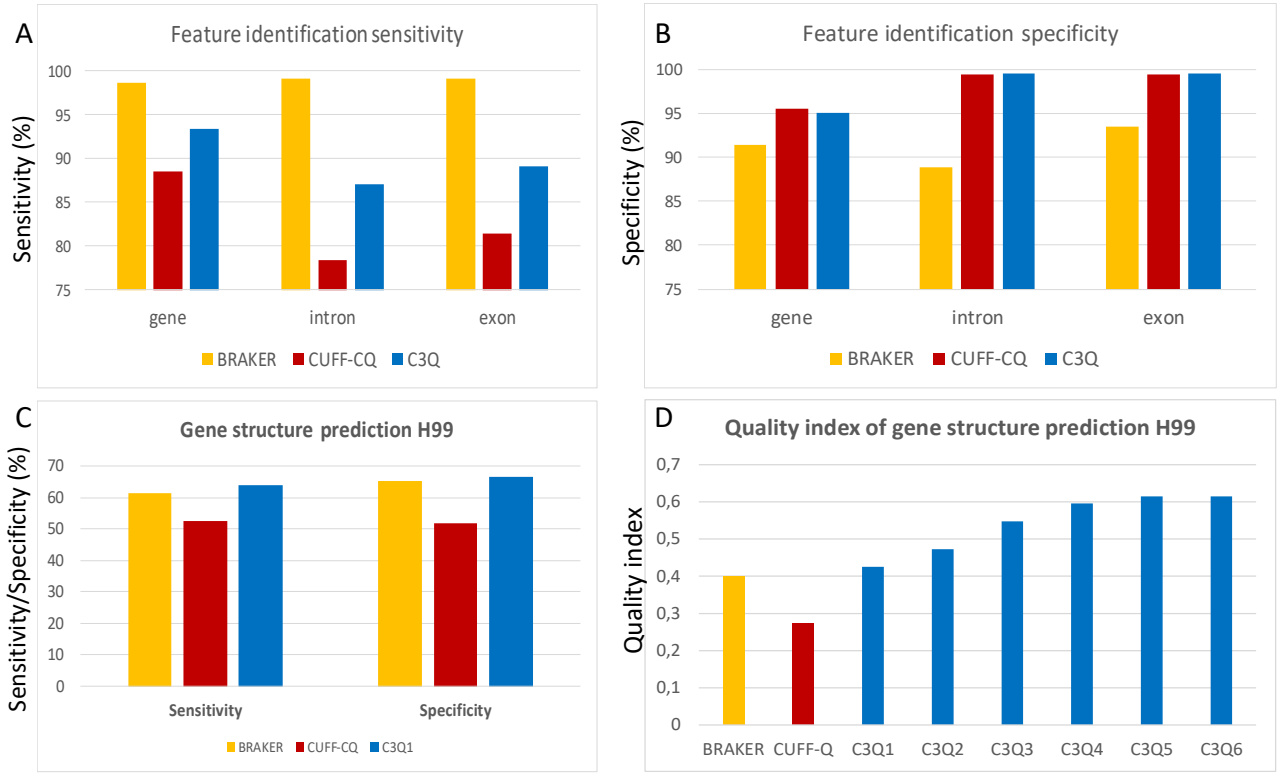
390 Figure 1. Schematic of the different pipelines tested in this study.
391

392 To compare the quality of these pipelines for identification of coding genes, we calculated
393 their sensitivity (percentage of coding genes present in the reference annotation overlapping with
394 one coding gene in the *de novo* annotation) and their specificity (percentage of predicted coding

395 genes overlapping with one coding gene in the reference annotation). These comparisons revealed
396 that BRAKER was much more sensitive than either Cufflinks-CodingQuarry protocol, missing only
397 91 coding genes in the *C. neoformans* genome (Figure 2A, Supplementary Table S1). However, the
398 BRAKER pipeline was less specific (91.4%), predicting 622 coding genes absent in the reference
399 annotation (Figure 2B). In contrast, both Cufflink-CodingQuarry protocols missed more coding
400 genes (743 and 447 genes for CUFF-CQ and C3Q protocols, respectively), but had a higher (95%)
401 specificity (Figures 2A,2B). We observed a similar pattern when we looked at CDS introns and CDS
402 exons within the identified references genes. Again, the BRAKER pipeline was very sensitive, with
403 only 0.4% missed introns (n=157) and 0.4% missed exons (n=164) in the prediction but had poor
404 specificity, with 4471 novel introns and 3065 exons predicted but not present in the reference
405 annotation (Figures 2A,B; Table S1). On the other hand, both Cufflink-CodingQuary-based
406 protocols missed more introns (n=4944 and n=3238 for CUFF-CQ and C3Q1 protocols,
407 respectively) and more exons (n=4281 and n=2777, respectively) but both were more specific,
408 predicting less than 200 introns or exons not present in the reference annotation. Overall, both
409 Cufflink-CodingQuary-based protocols returned more conservative results; they were more
410 specific in the predicted gene structures and identified a smaller number of new insertions (novel
411 exons/introns) and new genes. These more conservative predictions came at the cost of missing a
412 larger number of features than the BRAKER protocol.

413 To assess all of these performance parameters and select the highest-performing protocol
414 for further optimization, we considered the sensitivity and specificity of accurately predicting gene
415 structure (perfect exon/intron organization) for each of the three pipelines. The C3Q1 protocol
416 was the most sensitive, perfectly predicting the exon-intron layout of 66.5% (n=4516) of *C.*
417 *neoformans* H99 genes, compared to 65.2% and 51.9% perfect predictions from the BRAKER and
418 CUFF-CQ protocols, respectively (Figure 2C). This was also the most specific protocol with 63.9% of
419 the predicted genes perfectly fitting the reference gene structures, compared to 61.3% and 52.6%

420 of the predictions made by the BRAKER and CUFF-CQ protocols, respectively (Figure 2C). To better
421 compare the quality of these pipelines, we considered a quality index that multiplied the
422 sensitivity by the specificity of predicted gene structure predictions (Figure 2D). Our results
423 demonstrated that the C3Q1 pipeline was the best, with a quality index of 0.42. We performed the
424 same analysis with the *C. deneoformans* JEC21 genome annotation data and obtained similar
425 results, confirming the C3Q1 protocol was the best protocol for further optimization (Figure S1).



426

427

428 Figure 2: Sensitivity (A) and specificity (B) of the different tested pipelines for *C. neoformans* H99
429 genomic feature identification. For introns and exons, calculations were done using only genes
430 that were both identified by the pipelines and present in the reference annotation. (C) Sensitivity
431 and specificity of gene structure predictions using the three annotation pipelines. (D) Optimization
432 of the C3Q pipeline. C3Q1 is the pipeline using default settings. C3Q2 through C3Q6 refer to the
433 results obtained after each step of the pipeline optimization.

434

435 **Optimization of the C3Q1 pipeline**

436 *Effect of Cufflinks settings*

437 To improve both the number of perfectly predicted gene structures and the percentage of
438 predicted loci in perfect agreement with the reference coding gene structures, we considered 17
439 combinations of Cufflinks settings. We varied parameters including 1) the minimum distance
440 between transfags allowed to merge, 2) trimming of 3' ends of reads, 3) filtering of alignments
441 that lie within intronic intervals, 4) filtering of suspicious spliced reads, 5) minimum RNA-seq
442 fragments allowed to assemble transfags, and 6) filtering of alignments that lie within intronic
443 intervals in the same set of RNA-seq data. These Cufflinks parameter modifications reduced the
444 number of missed genes and increased the number of reference genes identified from 6348 to
445 6462 (Table S1). Using the final settings, the pipeline C3Q2 quality index reached a score of 0.473,
446 with 70.8% of reference gene intron-exon structures perfectly predicted and 66.8% of the
447 predicted genes perfectly matching the reference exon-intron gene structures (Figure 2D).

448

449 *Effect of the RNA-seq data set*

450 We tested the C3Q2 optimized pipeline using additional RNA-seq data obtained under five
451 different conditions in triplicate: stationary growth at 30°C (STAT30) and 37°C (STAT37),
452 exponential growth at 30°C (EXPO30) and 37°C (EXPO37), and growth under mating conditions
453 (Mating). Each RNA-seq data set generated a similar number of predicted transcripts, ranging
454 between 7049 genes using the STAT37 set up to 7199 loci using the EXPO30 data set (Table S1).
455 When compared to the reference set of genes, the number of predicted annotations were also
456 very similar (Table S1). As expected, including more samples improved the annotation quality. The
457 usage of the five conditions improved the C3Q3 annotation quality index to 0.547 despite the fact
458 that more predicted genes not present in the reference genome were identified using this pipeline

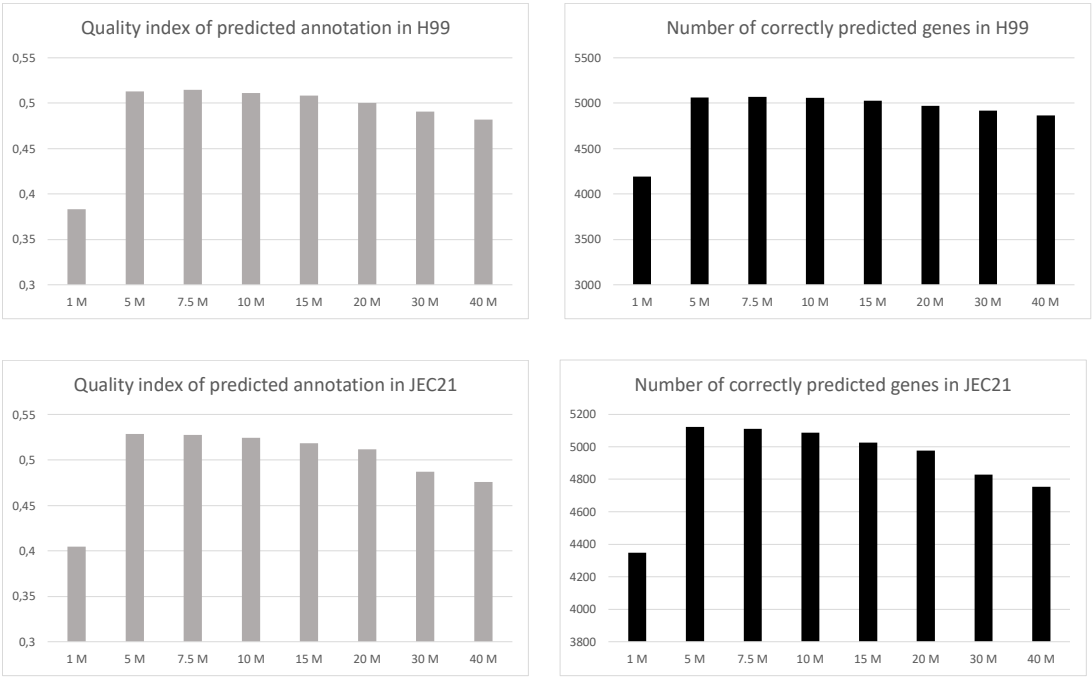
459 (n = 510) (Figures 2D, S2, Table S1). Similar results were obtained using the *C. deneoformans* JEC21
460 annotation and RNA-seq data (Figure S1, Table S1).
461

462 *Evaluation of RNA-Seq data set size in gene prediction quality*

463 Analysis of the results obtained using the C3Q2 pipeline fed with individual replicates of the
464 EXPO30 RNA-seq data counterintuitively suggested the size of the initial BAM file might be
465 negatively correlated with the quality of the final prediction (Tables S1). Identical analysis
466 performed with *C. deneoformans* RNA-seq gave a similar result, suggesting the sequencing depth
467 may substantially affect the quality of predictions and should be considered as a possible
468 parameter of optimization for gene prediction pipelines. To improve the analysis of the effect of
469 the size of the data set on the quality of gene prediction, the C3Q2 pipeline was tested with
470 different representative fractions of reads from a single EXPO30 replicate. Thus, replicate samples
471 with 1, 5, 7.5, 10, 15, 20, 30, and 40 million reads were used for *de novo* annotation of the *C.*
472 *neoformans* H99 genome, and the quality of the gene predictions were compared. We performed
473 this analysis using the same strategy for *C. deneoformans.* As shown in Figure 3, the quality of the
474 gene structure prediction was highly dependent on the size of the RNA-seq initial data set in both
475 species and strongly anti-correlated with the number of Cufflinks-assembled transcripts (Table S1).
476 The highest-quality predictions were obtained with replicate samples with only 5-10 million reads.
477 Using this adjusted read depth, the prediction showed improvement in nearly all parameters,
478 including for missed genes, missed exons, and missed introns (Table S1).

479 We adjusted the number of reads to 7.5 million for each replicate in each condition and
480 used these adjusted RNA-seq data sets for *de novo* annotation of the *C. neoformans* and *C.*
481 *deneoformans* reference genomes. As expected, the gene predictions obtained with the C3Q4
482 pipeline were further improved with a quality index of 0.593 and 0.596, for *C. neoformans* and *C.*

483 *deneoformans* annotations, respectively (Figure 2D, Figure S1, Table S1). In *C. neoformans*, 81.9%
484 of the reference gene structure was perfectly predicted and only 1.9% (n=129) of genes were
485 missed.



486

487 Figure 3. Effect of the size of the BAM file on the quality of the predicted annotation and on
488 the number of correctly predicted genes in *C. neoformans* H99 and *C. deneoformans* JEC21.

489

490 *Gene filtering*

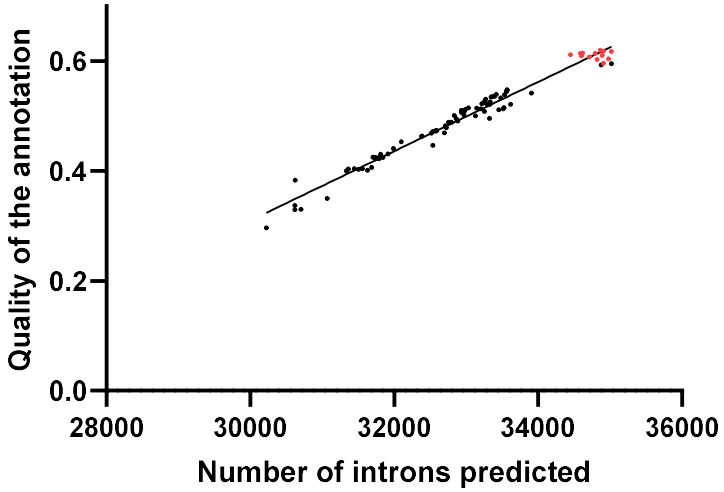
491 Each optimization step improving the quality of the gene prediction was also associated
492 with an increase of the number of predicted genes not present in the previously annotated
493 reference genome (Table S1). Using the C3Q5 protocol, 717 (703 loci) and 774 (762 loci) additional
494 genes were predicted in *C. neoformans* and *C. deneoformans*, respectively, compared to the
495 reference annotation. The majority of these genes are likely to be misannotations. One hundred
496 and six of the sequences had domain signatures of transposable elements, suggesting they
497 correspond to fragments of transposons or retrotransposons unannotated in the reference H99
498 genome. To filter out some of the novel predicted genes, we looked at their structure and

499 coverage. We compared the characteristics of these false-positive genes to the reference genes
500 and found that most novel predicted genes were short (219 nt mean length, 112 nt median
501 length), poorly expressed, and intronless. We tested different filters alone and in combination to
502 eliminate as many false positive genes as possible without affecting the number of correctly
503 predicted ones; the results are presented in Table S1. In both species, the best combination of
504 filters eliminated all spliced coding regions smaller than 150 nt, all intronless genes smaller than
505 300 nt, and all genome-predicted genes not supported by any RNA-seq reads. Due to the presence
506 secondary transcripts at some loci, many of which were generated due to differences in the RNA-
507 seq-predicted and genome-predicted transcripts for the same gene, a fourth filtering step was
508 performed. In this step, to ensure that there was only one transcript per loci, the longest RNA-seq-
509 predicted transcript or the longest genome-predicted transcript (for loci without RNA-seq
510 evidence) was selected as a representative for the gene CDS coordinates. After this fourth filtering
511 step, the number of predicted genes not present in the reference annotation was down to 409 and
512 427 genes in H99 and JEC21, respectively, and the quality index of the annotation increased to
513 0.614 and 0.608, respectively (Figures 2D, S1; Table S1).

514 *Exonerate-based recovery of missed genes*

515 Improvement of the pipelines was associated with an increase in the sensitivity of gene
516 identification. In the initial C3Q1 protocol, 447 reference genes were missed, whereas only 162
517 H99 genes and 132 JEC21 genes were missed with the C3Q5 pipeline. Blast2GO analysis of the
518 protein sequences encoded by the missed genes identified 16 proteins with conserved domains
519 suggesting that it might be possible to identify some of them through comparative sequence
520 analysis. Another 111 sequences were defined as hypothetical proteins. We first used the
521 sequence alignment program Exonerate (SLATER AND BIRNEY 2005) and the JEC21 reference
522 proteome as a reference to try to recover missed coding genes in H99. As expected, this analysis

523 identified a number of missed loci, but also added a number of unpredicted loci thus reducing the
524 quality of the annotation. In the final C3Q6 pipeline, we chose to restrict this Exonerate analysis to
525 genes that had been filtered out in the last step of the C3Q5 pipeline. We ultimately identified 14
526 and 9 novel genes in H99 and JEC21, respectively. Overall, the C3Q6 optimized pipeline was able to
527 identify nearly 98% of genes in H99, contributing only 410 (~6%) novel genes. Importantly, the
528 exon-intron structure of the predicted genes was predicted perfectly for >81% of the reference
529 genes in both species.
530
531 **Intron number is predictive of the quality of the C3Q6 predicted annotation**
532 During the course of the C3Q pipeline optimization, we obtained 88 versions of the H99
533 genome annotation. We carefully examined the different characteristics of these annotations,
534 looking for a parameter predictive of their quality. First, we plotted the number of predicted loci
535 against the quality of the annotation, but we did not observe any correlation. Similar results were
536 obtained when we looked at missed or novel loci, suggesting that these parameters were also not
537 indicative of the annotation quality. However, when the numbers of introns predicted were
538 plotted against the quality of the annotation, we obtained a linear correlation (Figure 4). This
539 correlation was lost during the filtration steps (red dots), which tend to reduce the number of
540 introns. Similar results were obtained for JEC21, suggesting that the number of introns is a good
541 parameter to consider when evaluating the quality of the annotation using the C3Q pipeline.



542

543 Figure 4. Relationship between the quality index of the H99 annotation and the number of introns
544 and transcripts predicted. The red points correspond to the filtering steps of the optimization
545 pipeline.

546

547

548

549 **Genome annotation of the *Cryptococcus deuterogattii genome***

550 We used the C3Q6 optimized pipeline to generate a new genome annotation for the *C.*
551 *deuterogattii* reference strain R265. This reference strain was isolated in 2001 from the
552 bronchoalveolar lavage fluid of an infected patient from the Vancouver Island outbreak (KIDD *et al.*
553 2004). Because of its outbreak origin and the loss of a functional RNAi pathway (D'SOUZA *et al.*
554 2011), *C. deuterogattii* has been the focus of a number of studies in recent years (CHENG *et al.*
555 2009; MA *et al.* 2009; NGAMSKULRUNGROJ *et al.* 2012; HUSTON *et al.* 2013; LAM *et al.* 2019). The R265
556 genome has been previously annotated three times (D'SOUZA *et al.* 2011; FARRER *et al.* 2015;
557 FERRAREZE *et al.* 2017), but a recent release of telomere-to-telomere genome sequence data (YADAV
558 *et al.* 2018) motivated us to generate an updated annotation. We generated RNA-seq data in
559 biological triplicate from cells grown under five conditions (exponential growth phase at 30°C and

560 37°C, stationary growth phase at 30°C and 37°C, and under mating conditions) as previously
561 described for *C. neoformans* H99 and JEC21 (WALLACE *et al.* 2020). Reads were trimmed, aligned to
562 the reference genomes (Table S2), and input into the optimized C3Q6 genome annotation
563 pipeline.

564 To gain further insight into the quality of our updated R265 annotation, the structure
565 predictions of genes for *C. deuterogattii* R265 chromosomes 9 and 14 were manually curated
566 through visual examination of read alignments using Artemis (CARVER *et al.* 2012) as previously
567 described (JANBON *et al.* 2014; GONZALEZ-HILARION *et al.* 2016). We compared this manually curated
568 annotation of chromosomes 9 and 14 with the prediction obtained from the C3Q6 genome
569 annotation pipeline of these two chromosomes. This analysis revealed a quality index of this
570 annotation of 0.51, with 68% of all predicted loci correctly predicted and 75% of the manually
571 curated genes on these two chromosomes correctly predicted. In *C. neoformans* and *C.*
572 *deneoformans*, the C3Q6 genome annotation pipeline missed very few genes (1.4% missed) and
573 predicted a small number of false-positive genes (6.3%) (Table S3). As expected, the quality of the
574 C3Q6 annotation was much better than previously published annotations (FARRER *et al.* 2015;
575 FERRAREZE *et al.* 2017) (Table S3).

576 **Manual curation of R265 annotation**

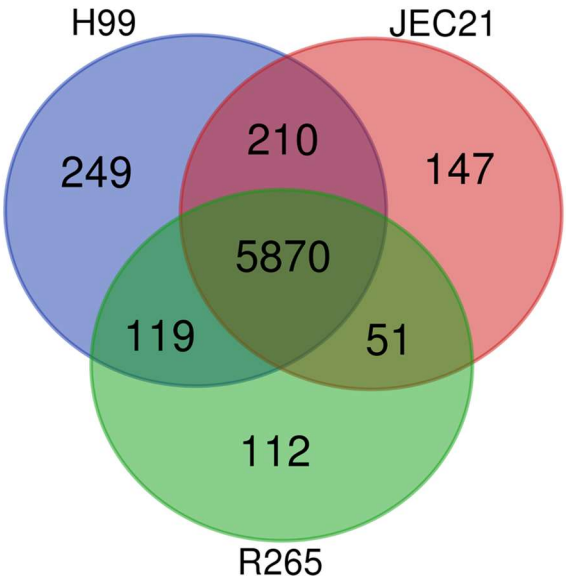
577 To systematically analyze critical points of the automated *C. deuterogattii* R265 gene
578 prediction, four sets of data were evaluated and selected for manual correction: 1) Exonerate-
579 retrieved sequences (deleted and non-predicted), 2) predicted novel loci, 3) genes predicted in
580 merged/split loci, and 4) small and potential pseudogenes. During the course of this manual
581 curation of chromosomes 9 and 14, visual examination of the aligned reads revealed a number of
582 loci at which the genome sequence did not entirely align with the RNA-seq reads, suggesting there
583 were errors in the reference genome assembly. These errors were responsible for gene shortening

584 or splitting and might partially explain the lower quality index score calculated for the R265
585 predicted annotation of chromosomes 14 and 9 compared to the quality scores obtained using
586 similar data from JEC21 and H99. To systematically identify these types of annotation mistakes, we
587 compared the size of the *C. deuterogattii* R265 predicted genes with their *C. neoformans* H99/*C.*
588 *deneoformans* JEC21 orthologous counterparts. We identified 729 genes in R265 that were
589 significantly smaller than their *C. neoformans* and *C. deneoformans* orthologues (size ratio < 0.8).
590 Visual examination of these loci revealed that most of them were incorrectly predicted and
591 needed manual curation. Manual curation was also performed for 67 genes that were significantly
592 smaller than only one of their orthologues (*C. neoformans* or *C. deneoformans*). This manual
593 curation also identified 125 genes which would have otherwise been challenging to predict due to
594 genome sequence errors mistakenly affecting orthologue size ratios (Table S4).
595 Overall, our new version of R265 genome annotation contains 6,405 coding genes with
596 33,619 introns in CDS regions (34,512 introns including the UTRs). The manually corrected genes
597 from chromosomes 9 and 14 were added and replaced the predicted genes from these regions,
598 improving the quality of the final annotation. Of the 6,405 genes predicted with the C3Q6 pipeline,
599 the CDS structure was modified for 873 coding through manual curation. Annotation of 3'UTR
600 and/or the transcript leader sequence was performed for 1210 genes from the manually curated
601 chromosomes (9 and 14) and the 873 manually curated genes with modified CDS structures.
602 Furthermore, we annotated 55 lncRNAs and used tRNAscan (LOWE AND CHAN 2016) to annotate 161
603 tRNAs (Table S3). We also removed all genes predicted to reside within centromeric regions, and
604 used previously published, manually curated annotations for these regions (YADAV *et al.* 2018).
605

606 **Putative pseudogenes and missing genes**

607 We compared the gene content across the three annotated *Cryptococcus* genomes. We
608 identified 5870 ortho-groups common to all three species (Figure 5). We found a similar number

609 of R265-specific genes to the number of specific genes identified in H99 and JEC21, which is likely
610 an indicator of the high quality of this annotation. Of interest, this analysis revealed 210 ortho-
611 groups missing in *C. deuterogattii* R265, but present in both the *C. neoformans* H99 and the *C.*
612 *deneoformans* JEC21 genomes (Table S5). This list of genes was curated first through Exonerate-
613 based analysis and then through manual examination of the syntenic loci.
614



615
616 Figure 5. Comparative gene content of the annotated *C. neoformans* H99, *C. deneoformans* JEC21,
617 and *C. deuterogattii* R265 genomes. Ortho-groups specific or common to the different species
618 were identified and numbered.
619
620
621 *C. deuterogattii* R265 has previously been shown to lack a functional RNA interference
622 pathway (D'Souza *et al.* 2011; Billmyre *et al.* 2013). Accordingly, the genes encoding one Dicer
623 (*DCR1*) and an Argonaute protein (*AGO1*) have been lost, and the genes encoding an RNA
624 dependent RNA polymerase gene (*RPD1*) and an RNAi essential zinc finger protein (*ZNF3*) are
625 truncated and probably not functional in this strain (D'Souza *et al.* 2011; Feretzaki *et al.* 2016). The

626 identification of truncated or absent genes in the R265 genome has been as a strategy to identify
627 additional, novel components of the RNAi pathway in *C. neoformans* (FERETZAKI *et al.* 2016). To
628 identify genes specifically lost in *C. deuterogattii*, we considered the genes not predicted by our
629 pipeline but present in the other *Cryptococcus* species annotations available in FungiDB (BASENKO
630 *et al.* 2018; FARRER ET AL. 2015; D'SOUZA ET AL. 2011). We considered here *C. tetragattii* strain
631 IND107, *C. bacillisporus* strain CA1873, and *C. gattii* strains WM276, NT-10, and EJB2; no *C.*
632 *decagatiii* annotation was available at the time of this study. We identified 17 ortho-groups that
633 were absent in the R265 genome but present in all other species (Table 1). As expected, one
634 ortho-group corresponds to an Argonaute protein (ortho-group OG0000415). We also confirmed
635 that the gene *FCZ28,* which encoded a transcription factor essential for the sex-induced-silencing
636 RNAi pathway in *C. neoformans*, was specifically absent in the R265 genome (FERETZAKI *et al.* 2016).
637 In contrast, the gene *GWO1*, previously identified as specifically lost in R265 and coding for an
638 Ago1-interacting protein (although deletion mutants have normal siRNA profiles) was not present
639 in this new list due to its absence in the IND107 genome (DUMESIC *et al.* 2013). The orthologue size
640 ratio analysis performed to pinpoint genome sequence mistakes eventually identified 119 R265
641 genes with a size ratio lower than 0.8 compared to both *C. neoformans* and *C. deneoformans*
642 orthologs or shortened in one species and absent in the other (Tables 2; S7). Although some loci
643 are likely pseudogenes, we decided not to annotate them as such because there is no strict
644 structural definition of what constitutes a pseudogene (TUTAR 2012) and we cannot evaluate the
645 functionality of a gene based on its structure alone.
646

H99 gene ID	R265 gene ID	Size ratio	Putative function	Role in RNAi	ref
CNAG_00505	absent		transcription factor (*FZC28*)	yes	(1)
CNAG_01061	absent		serine/threonine protein kinase (*FRK102*)	?	(2)
CNAG_02207	absent		glycosyl hydrolase	?	
CNAG_03734	absent		chromodomain-containing protein (*CDP1*)	?	(1)
CNAG_04016	absent		Identified spore protein 5 (*ISP5*)	?	(3)
CNAG_04596 , CNAG_04619	absent		prolyl endopeptidase	?	
CNAG_04609	absent		Argonaute protein (*AGO1*)	yes	(4)
CNAG_05158	absent		hypothetical protein	?	-
CNAG_05265	absent		hypothetical protein	?	
CNAG_05449	absent		copper metallothionein 1 (*MTN1*)	?	(5)
CNAG_05657	absent		2,4-dienoyl-CoA reductase	?	
CNAG_06233	absent		hypothetical protein	?	
CNAG_06395	absent		hypothetical protein	?	
CNAG_06609	absent		2-polyprenyl-6-methoxyphenol hydroxylase (*ORX1*)	?	(1)
CNAG_07556	absent		hypothetical protein	?	
CNAG_07702	absent		F-box containing protein	?	
CNAG_07959	absent		GTPase-activator protein (GAP)	?	
CNAG_03466	CNBG_2143	0.083	RNA-dependent RNA polymerase 1 (*RDP1*)	yes	(4)
CNAG_02700	CNBG_9326	0.092	C2H2-type zinc finger transcription factor (*ZNF3*)	yes	(1)
CNAG_01423	CNBG_5946	0.102	*QIP1*	yes	(6)
CNAG_04146	CNBG_2894	0.121	SET domain-containing protein	?	
CNAG_06486	CNBG_4982	0.137	*GWC1*	yes	(6)
CNAG_03911	CNBG_9603	0.139	carboxylesterase domain-containing protein	?	
CNAG_06497	CNBG_4974	0.162	microsomal epoxide hydrolase (*MEH1*)	?	(1)
CNAG_01992	CNBG_2960	0.190	SET domain-containing protein	?	
CNAG_03117	CNBG_2464	0.191	hypothetical protein	?	
CNAG_07344	CNBG_9031	0.197	Ras guanyl-nucleotide exchange factor	?	
CNAG_01406	CNBG_5961	0.198	hypothetical protein	?	
CNAG_03414	CNBG_10064	0.201	REX4-like exonuclease domain containing protein	?	
CNAG_04184	CNBG_2860	0.224	transcription factor (*FZC47*)	no	(1)
CNAG_03193	CNBG_9232	0.233	hypothetical protein	?	
CNAG_04400	CNBG_9268	0.234	Ribosomal protein S10p/S20e	?	
CNAG_03938	CNBG_5530	0.243	*Cryptococcus* pheromone receptor 2 (*CPR2*)	yes	(1)
CNAG_00123	CNBG_9042	0.286	hypothetical protein	?	
CNAG_06159	CNBG_4866	0.315	hypothetical protein	?	
CNAG_01004	CNBG_0584	0.316	Rho/Rac/Cdc42-like GTPases	?	
CNAG_06509	CNBG_4963	0.318	hypothetical protein	?	

Table 2: Genes with putative or known roles in RNAi identified as genes of H99 with orthologues in all *Cryptococcus* species but absent or severely truncated in *C. deuterogattii* R265 as compared to JEC21 and H99 (proteins with a ratio <0.33 are presented. The full table of shortened genes is presented as Table S6). (1) FERETZAKI et al 2016; (2) Lee et al. 2016; (3) HUANG et al. 2015; (4) WANG et al. 2010 ; (5) DING et al. 2011 ; (6) DUMESIC et al. 2013.

656

657 As expected, the RNAi genes *RPD1 (WANG et al. 2010)*, *ZNF3 (FERETZAKI et al. 2016)*, *CPR2*
658 *(FERETZAKI et al. 2016)*, *QIP1 (DUMESIC et al. 2013)*, *GWC1 (DUMESIC et al. 2013)*, *RDE4,* and *RDE5*
659 (BURKE *et al.* 2019) were present in this list, confirming that a large number RNAi genes are not
660 functional or are absent in R265. Conversely, *RDE1*, *RDE2,* and *RDE3* (BURKE *et al.* 2019), which
661 were recently implicated in RNAi in *C. neoformans*, all possess an orthologue of similar size in R265
662 (CNBG_3369, CNBG_4718, and CNBG_1922, respectively). Of note, in this version of the R265
663 annotation, the *DMT5* (CNBG_3156) gene encoding a putative DNA methyltransferase is not
664 truncated as previously published (YADAV *et al.* 2018; CATANIA *et al.* 2020) and appears to be
665 expressed and functional.

666

667 **Gene organization, antisense transcription, and alternative splicing in R265**

668 The absence of RNAi in R265 was recently shown to be associated with a modification of
669 the chromosome structure: shorter centromeres and the loss of any full-length transposable
670 elements (YADAV *et al.* 2018). Here, we examined the possible consequences of RNAi loss on the
671 transcriptome aside from the expected absence of siRNA. We first hypothesized that the absence
672 of RNAi in *C. deuterogattii* could result in increased antisense transcription, as it might be the
673 source of double-stranded RNA; increased antisense transcription in RNAi-deficient species has
674 also been observed in *Saccharomyces* species (ALCID and TSUKIYAMA 2016). We thus evaluated the
675 sense/antisense transcript ratio at coding gene loci. Because the 3'UTR and TL sequences were
676 only partially annotated in the R265 genome, we restricted our analysis to the CDS regions. We
677 compared the ratio of read numbers of sense and antisense transcripts corresponding to all coding
678 regions in *C. neoformans*, *C. deneoformans,* and *C. deuterogattii* under four growth conditions.
679 When cells were grown to exponential growth phase at 30°C (E30), most of the expressed genes

680 (92.2 %) had antisense transcription in *C. neoformans*, but antisense transcripts were expressed at
681 a very low level (1.2% of transcription antisense *vs* sense). Antisense transcription prevalence and
682 expression levels were similar in the two other species (92.6% and 95.2% of genes with antisense
683 transcription, 3.2% and 2.5% of antisense *vs* sense transcription in *C. deneoformans* and *C.*
684 *deuterogattii,* respectively). These ratios changed in different growth conditions, particularly
685 increased temperature at both exponential and stationary growth phase. However, this analysis
686 did not provide evidence of a link between the level of antisense transcription and the absence of
687 RNAi in R265 because the RNAi-proficient JEC21 strain had the highest antisense/sense
688 transcription ratio across all conditions tested (Figure 6).

689 We then analyzed gene orientation in the three species, evaluating the number of genes
690 coupled in a tail-to-tail orientation as this orientation should favor antisense transcription over
691 head-to-tail or head-to-head orientations. Indeed, as shown in Figure 6B, there was a clear
692 selection against tail-to-tail gene orientation in *C. deuterogattii*, thus limiting antisense
693 transcription (c-squared = 103.79, df = 4, p-value < 2.2e-16). In contrast, this orientation is favored
694 in JEC21, which might explain the higher level of antisense transcription.

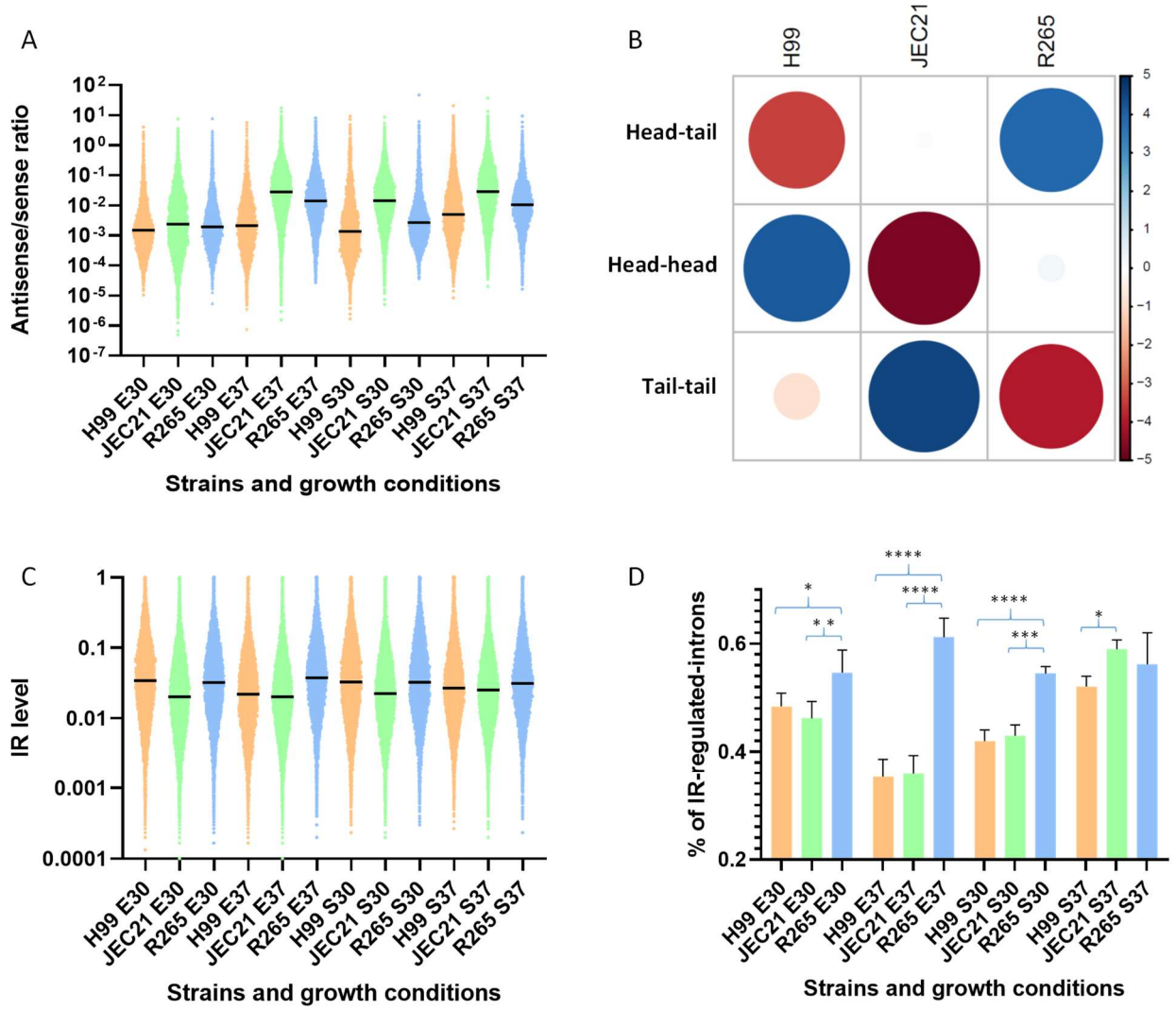
695 The SCANR model predicts that siRNAs are produced in response to poorly spliced introns
696 that stall the spliceosome complex, which should result in lower levels of expression for the
697 corresponding gene (DUMESIC *et al.* 2013). To explore whether loss of RNAi could have affected
698 intron retention (IR) in *C. deuterogatiii*, we compared the number of CDS introns regulated by
699 intron retention in this species and two RNAi-proficient ones. Interestingly, in three conditions the
700 percentage of introns regulated by IR was higher in R265 than in JEC21 or H99 (Figure 6C). For
701 instance, when cells were grown to exponential phase at 37°C, 44.5% of R265 introns are
702 regulated by IR as compared to 21.7% and 20.8% in *C. neoformans* and *C. deneoformans*,
703 respectively. In contrast, the IR indices were similar across the three species when cells were
704 grown at 30°C. However, at 37°C in either exponential and stationary growth phase, the median

705 value of the IR index in R265 was higher than those in both *C. neoformans* and *C. deneoformans*.

706 Overall, these data suggest that IR is better tolerated in R265 than in H99 or JEC21; this result

707 aligns with the SCANR model of siRNA production and gene regulation in *Cryptococcus*.

708



709

710 Figure 6. (A) Antisense/sense transcription ratios in *C. neoformans* (H99), *C. deneoformans* (JEC21)

711 and *C. deuterogattii* (R265). RNA-seq data obtained from cells grown to exponential phase at 30°C

712 (E30) and 37°C (E37) or stationary phase at 30°C (S30) and 37°C (S37) were used. (B) Statistical

713 analysis (Pearson's Chi-squared test) revealed a species-specific bias in gene orientation. Circle size

714 is proportional to the standardized residuals, with absolute values higher than 2 representing

715 statistical significance (Sharpe 2015). Positive values (blue circles) in cells specify a positive

716 association between the corresponding row and column variables. Negative residuals are
717 represented by red circles. This implies a negative association between the corresponding row
718 and column variables. (C) Intron retention level in each species according to growth condition.
719 Black bars represent median values. (D) Percentage of CDS introns regulated by IR in each species
720 according to growth condition. The results of the statistical analysis (ANOVA one-way multi-
721 comparison analysis corrected by FDR). * (q value < 0.05), ** (q value < 0.01), *** q value <0.001),
722 **** (q value < 0.0001).
723

724 **Subtelomeric gene organization and cluster exchange in *Cryptococcus***

725 Our analysis identified 210 orthologue groups present in both *C. neoformans* and *C.*
726 *deneoformans* but absent in *C. deuterogattii*. Interestingly some of these lost genes are clustered
727 in these genomes. We identified 21 clusters of lost genes with consecutive elements in both *C.*
728 *neoformans* and *C. deneoformans* reference genomes. One of these lost clusters has been
729 previously described and has been reported to contain homologues of several *GAL* genes (*GAL1*,
730 *UGE2*, and *GAL7*) and a gene encoding a sugar transporter of the major facilitator superfamily
731 (MFS) (CNAG_07897) (SLOT AND ROKAS 2010). We also identified a fifth gene in this cluster
732 (CNAG_06055) which encodes a putative alpha-1,4-galactosidase (Figure S2A). *C. neoformans* and
733 *C. deneoformans* also possess unclusterered paralogues of the genes *UGE2* (*UGE1*, CNAG00697),
734 *GAL1* (*GAL101*, CNAG_03946), and *GAL7* (*GAL701*, CNAG_03875). Previous studies have shown
735 *UGE2* is required for growth on galactose, whereas it paralogous gene *UGE1* is necessary for
736 growth at 37°C and glucuronoxylomannogalactan (GXMGal) biosynthesis, which makes up an
737 important fraction of the *Cryptococcus* polysaccharide capsule (MOYRAND *et al.* 2008). Interestingly,
738 we previously reported that a *uge2Δ* mutant strain was able to grow on galactose at 37°C,
739 suggesting that *UGE1* is able to compensate in the absence of *UGE2* at 37°C. The GAL cluster with

740 five genes has also been lost in all other *Cryptococcus* species that were assessed. Thus, the *C.*
741 *gattii* clade species possess the only non-clustered paralogues of the GAL pathway; yet, they are
742 all able to grow on galactose as a sole carbon source, suggesting these genes are involved in both
743 GXMGal synthesis and galactose assimilation in this species (Figure S2B).

744 Gene ontology (GO) term enrichment analysis (PRIEBE *et al.* 2014) of 52 genes within 18
745 non-subtelomeric clusters that were absent in R265 revealed a statistically significant enrichment
746 of genes coding for proteins implicated in transport and transcription regulation (Figure 7A).
747 Functional annotation of these genes confirmed this result (Table S7). We identified 13 clusters
748 containing at least one gene coding for a putative transporter, including six MFS-type transporters,
749 and eight clusters containing at least one gene coding for an annotated or putative transcription
750 factor (TF), including six fungal Zn(2)-Cys(6) binuclear cluster domain-containing TFs. Overall,
751 seven clusters contain both a transporter and a TF (Figure 7B, Figure S3). Strikingly, this association
752 between transporters and TFs resembles the organization of primary metabolic gene clusters
753 (MGCs) (ROKAS *et al.* 2018). Because three MGCs were located within subtelomeric loci, we
754 compared the gene content within subtelomeric regions to the gene content of the lost clusters.
755 We considered the 20 most distal genes of each chromosome arm in H99. GO term enrichment
756 analysis of these 560 H99 subtelomeric genes revealed very similar profiles to the profiles
757 obtained for the cluster genes. Again, genes coding for proteins implicated in transport in
758 subtelomeric regions were significantly enriched (Figure 7C).

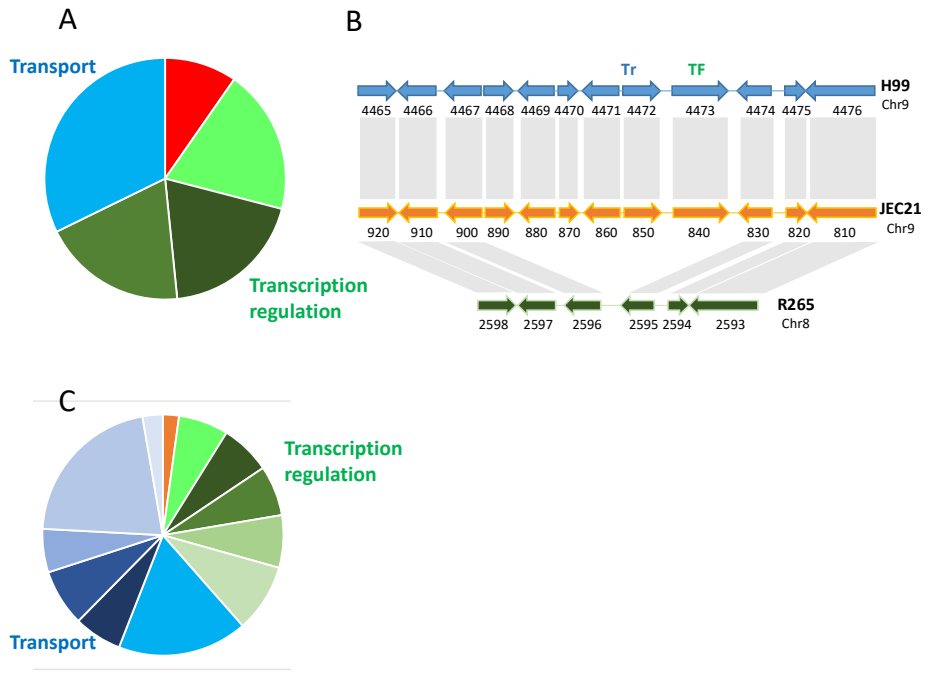


Figure 7. (A) GO term enrichment analysis of genes in clusters absent in R265. Green colors indicate GO terms associated with transcription regulation (GO:0006012, GO:0000981, GO:0006366, GO:0006357). Blue colors indicate GO terms associated with transport (GO:0055085). Orange colors indicate GO terms associated with galactose metabolism (GO:0006012). (B) Example of the organization of an MGC-like cluster absent in R265. CNAG_04468 (CNI00890) encodes a putative tartrate dehydrogenase, CNAG_04469 (CNI99880) encodes a putative 4-aminobutyrate transaminase, CNAG_04470 (CNI00870) encodes a putative halo-acid dehalogenase, CNAG_04471 (CNI00860) encodes an FAD-dependent oxidoreductase superfamily protein, CNAG_04472 (CNI00850) encodes an MFS protein, and CNAG_04473 (CNI00840) encodes a TF with a fungal Zn(2)-Cys(6) binuclear cluster domain. (C) GO term enrichment analysis of subtelomeric genes in H99. Green colors indicate GO terms associated with transcription regulation (GO:0051213, GO:0000981, GO:0006366, GO:0006357, GO:0006351, GO:0006355). Blue colors indicate GO terms associated with transport (GO:0055085, GO:0022891, GO:0022857, GO:0005215, GO:0016021, GO:0008643, GO:0006810). The orange color indicates a GO term associated with dioxygenase activity (GO:0051213).

775

776 Functional annotation of these subtelomeric genes confirmed this enrichment of transporters and
777 TFs (Table S8). We found an unexpected number of genes encoding annotated or putative TFs (n =
778 33) and transporters (n = 68) within these regions of the H99 genome. Most of these TFs and
779 transporters belong to the fungal Zn(2)-Cys(6) binuclear cluster domain-type (n= 24) and MFS-type
780 (n= 49) families, respectively. Comparison of the organization of *C. neoformans* H99 subtelomeric
781 loci to those in *C. deneoformans* JEC21 revealed a very similar organization, and only four mosaic
782 subtelomeric regions were identified with genes from at least two different regions in H99; few
783 genes were present in H99 but absent in JEC21 (Figure 8). However, we did identify two duplicated
784 regions in the JEC21 subtelomeric regions. The first duplicated locus consists of six genes with
785 orthologues in subtelomeric region of the left arm of Chr 5 in H99, and these genes have been
786 duplicated such that this set is present in both subtelomeric regions of chromosome (Chr) 5. The
787 second duplicated region has been previously described (FRASER *et al.* 2005). It is located in the left
788 arms of Chrs 8 and 12 and resulted from a telomere-telomere fusion that occurred during the
789 construction of the JEC20/JEC21 congenic mating pair. It contains 20 coding genes and the H99
790 orthologues are syntenic, but they located more than 200 kb from the end of the right arm of Chr
791 4 (coordinates 815320 to 878026). Interestingly, a TF with a fungal Zn(2)-Cys(6) binuclear cluster
792 domain (*FZC2*, CNAG_05255) and a putative amino acid transporter (CNAG_05254) are present
793 within this repeated region. Conversely, genes in the subtelomeric regions of the right arms of H99
794 Chrs 4 and 14 are orthologues of genes located within a central part of JEC21 Chr 8 (Figure S3),
795 suggesting an additional telomere-telomere fusion event. In contrast, the subtelomeric regions in
796 R265 have undergone more rearrangements compared to JEC21 – in R265 there are fifteen mosaic
797 subtelomeric regions that contain genes from at least two different regions in H99. We also
798 identified nine genes within six R265 subtelomeric regions whose orthologues are located far from
799 the telomeres in H99. Interestingly, functional annotation of the R265-specific subtelomeric gene

800 clusters (n = 12) (Figure 8; Table S9), revealed an enrichment of genes encoding TFs (n = 2) and

801 transporters (n = 6).

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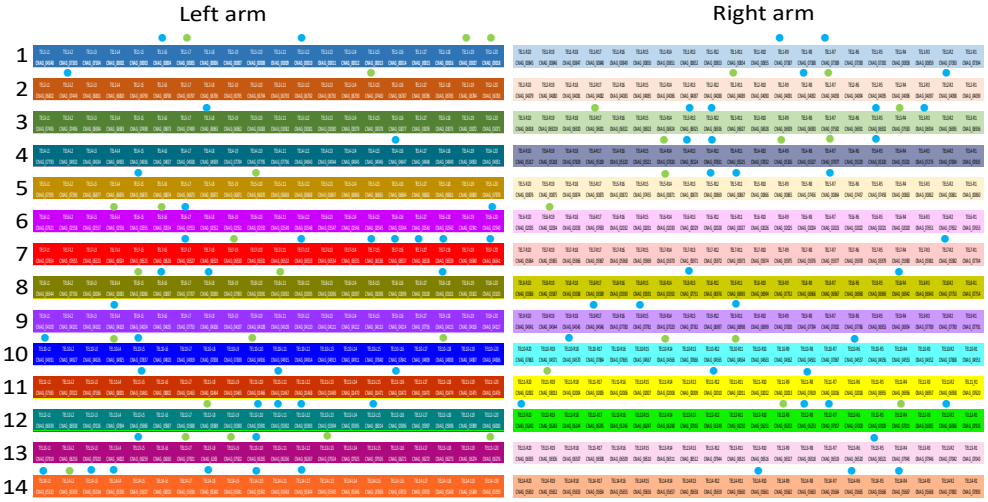
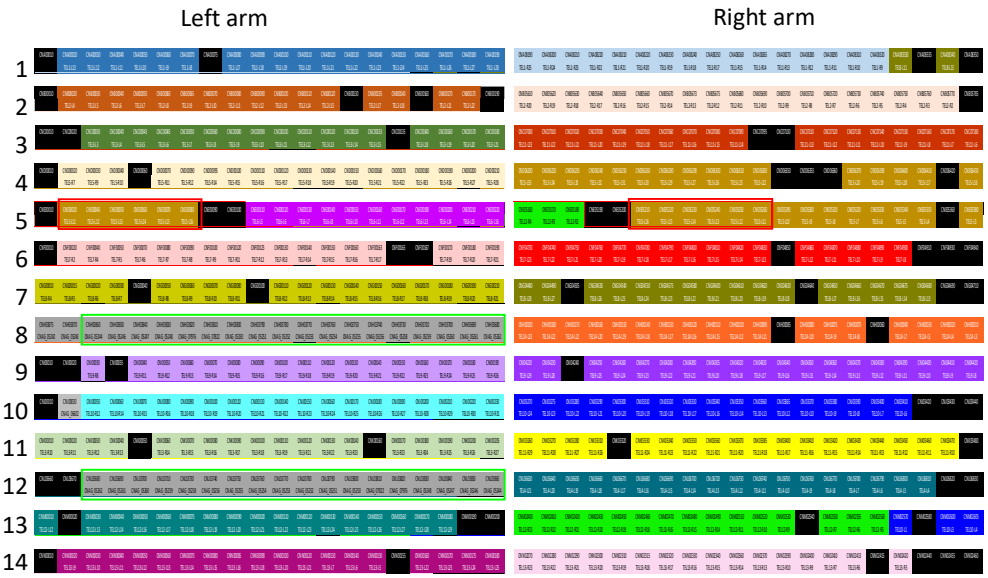
C. neoformans H99

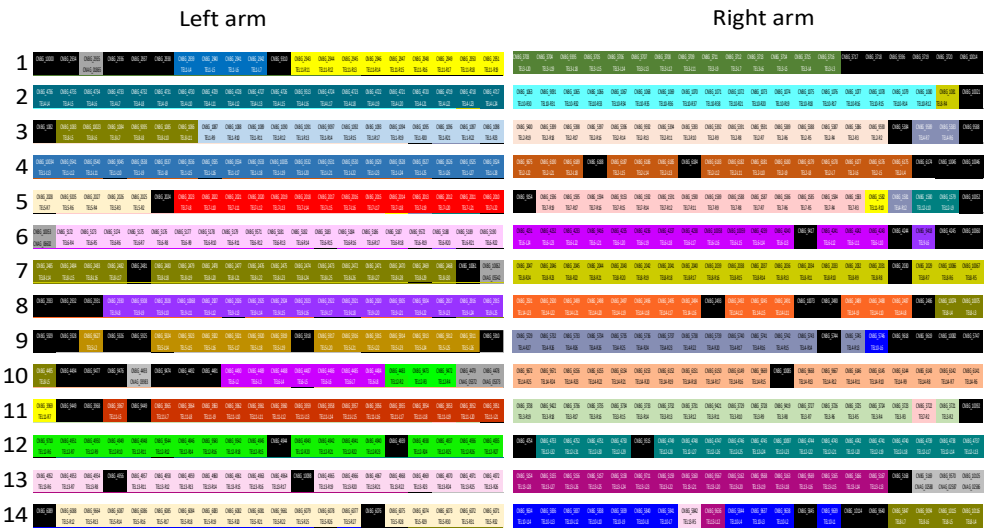


C. deneoformans JEC21



duplication

C. deuterogattii R265



812 Figure 8. Subtelomeric gene organization in *Cryptococcus*. The 20 most distal genes at each
813 subtelomeric locus were considered. The color code identifies each subtelomeric regions in H99
814 and orthologous genes in the other species. The positions of these orthologues in the H99
815 subtelomeric regions are given (TEL-RX or TEL-LX correspond to genes positioned within the right
816 or left arm of chromosome X). When the orthologous gene is not located within a subtelomeric
817 region, its locus named is given. Black boxes correspond to genes present in *C. deneoformans* or *C.*
818 *deuterogattii* but absent in *C. neoformans*. Red and green boxes indicate duplicated sets of genes.
819 Blue dots indicate transporters. Green dots indicate transcription factors.
820
821 Subtelomeric regions have been shown to be silenced by H3K27me3 histone modifications in *C.*
822 *neoformans*, and a large number of genes that are upregulated upon deletion of the H3K27
823 methyltransferase (encoded by *EZH2*) are located within subtelomeric regions (DUMESIC *et al.*
824 2015). Accordingly, we observed that expression of the 580 most proximal genes was generally
825 lower than the expression of the most telomere-distal genes (Figure 9). Interestingly, we found
826 that the H99 genes present within the MGCs that were lost in R265 were also poorly expressed.
827 However, none of these genes were upregulated upon *EZH2* deletion (DUMESIC *et al.* 2015),
828 suggesting that they are not directly regulated by H3K7me3. In summary, these data suggest that
829 dynamic exchanges of MGCs between subtelomeric regions occurred during *Cryptococcus*
830 speciation. These results also suggest that MGC exchanges between subtelomeric loci and more
831 central parts of chromosomes might be associated with new assimilation capacities.
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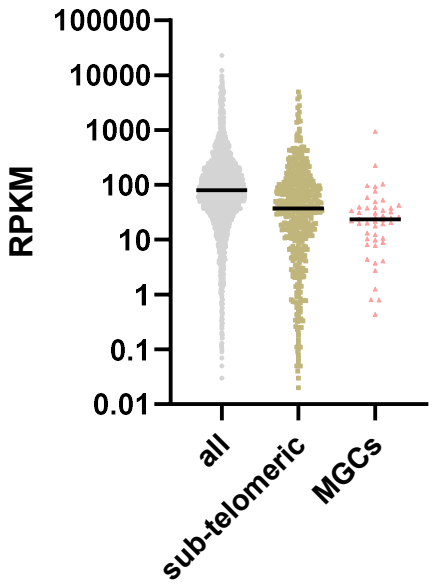

833

834 Figure 9. Expression of genes according to their position on the chromosome. Subtelomeric genes

835 are the 20 most distal genes of each chromosome arm. The H99 genes present within the non-

836 subtelomeric cluster of genes lost in R265 are indicated as MGCs.

837

838

839 **Discussion**

840 Although a number of bioinformatic pipelines have been published in recent years,
841 accurate annotation of fungal genomes is still difficult due their complexity and compactness (HAAS
842 *et al.* 2011). In this study, we have carefully optimized a previously published Cufflinks-
843 CodingQuarry-based annotation pipeline and tested it on two complex fungal genomes. This
844 pipeline largely outcompeted the BRAKER1 pipeline when applied to two *Cryptococcus* reference
845 genomes (*C. neoformans* H99 and *C. deneoformans* JEC21) and would likely outcompete many
846 other pipelines use to annotate fungal genomes *de novo* (MIN *et al.* 2017).

847 Our optimization process revealed three notable points. First and counterintuitively,
848 increasing the quantity of data did not always result in a better annotation. This is likely because
849 Cufflinks tends to make huge clusters when large data sets are input; these clusters might be
850 eliminated during the transcript identification step. Accordingly, we found that the number of
851 predicted transcripts decreased when too much data was used. Second, we found a nearly linear
852 relationship between the number of introns predicted and the quality of the annotation. However,
853 this correlation did not hold when two of the pipelines were compared; the BRAKER pipeline
854 predicted more introns than the C3Q pipeline, along with predicting many more genes.
855 Nevertheless, the correlation between intron number and annotation quality provided a facile way
856 to evaluate the reliability of a *de novo* annotation, which might be affected, for instance, by the
857 quality of the RNA-seq data. Third, we found the final step of comparative genomics did not
858 always improve the quality of the annotation. In our assay, the Exonerate-based analysis step
859 using the whole proteome of a reference species primarily introduced errors into the annotation.
860 This was probably due to the fact that even when manually curating genome annotations, a
861 number of dubious genes remain, which are then transferred to the new genome annotation. In

862 fact, a systematic usage of a comparative annotation step following a *de novo* RNA-seq annotation
863 would likely result in a dramatic expansion of dubiously annotated genes in fungal genomes.

864 During the annotation of the R265 genome, we manually curated a subset of genes that
865 were lost in R265 compared to all of the other *Cryptococcus* species as well as a set of putative
866 pseudogenes. The identification of genes specifically lost or pseudogenized in R265 has previously
867 been used as a strategy to identify novel RNAi components in *C. neoformans* (FERETZAKI *et al.* 2016).
868 Accordingly, most known RNAi genes are present in these sets of lost and pseudogenized genes
869 (BILLMYRE *et al.* 2013). However, some genes, like *RDE1* (BURKE *et al.* 2019), which is necessary for
870 siRNA production, are present and functional in R265, suggesting that it may have roles
871 independent from RNAi silencing. On the other hand, *GWO1*, which is also considered to be an
872 RNAi pathway component, is also absent in the *C. tetragattii* strain IND107 and is therefore absent
873 in our list as well. One possible explanation is that Gwo1 alone or in complex with Ago1 could play
874 another role independent of RNAi. Another possibility is that a Gwo1-dependent RNAi pathway
875 has also been lost in *C. tetragattii*. Nevertheless, this analysis confirms that looking for specific
876 gene loss in a fungal species deficient for a certain pathway remains a promising strategy for the
877 identification of genes implicated in this pathway in other proficient species. In the present case, it
878 would be interesting to see how many of the R265 truncated genes are functional in other *C. gattii*
879 species, although it would demand a complex manual curation, which is beyond the scope of this
880 paper.

881 Our study revealed that loss of RNAi in R265 is associated with few general transcriptome
882 modifications compared to the transcriptomes of JEC21 and H99, aside from the predictable
883 absence of siRNA. This might be because we did not annotate most non-coding features like
884 lncRNAs, transcript leaders, and 3'UTRs. Yet, quantification of the sense/antisense transcription
885 ratio at CDS did not reveal any differences between R265 and the other *Cryptococcus* species

886 analyzed, suggesting that this ratio does not depend on the RNAi status of the species in this
887 genus. This is in agreement with the fact that siRNAs in *C. neoformans* primarily target transposons
888 and retrotransposons (JANBON *et al.* 2010; WANG *et al.* 2010; DUMESIC *et al.* 2013), whereas
889 antisense transcription is associated with nearly all of the genes as we have shown. This result also
890 suggests antisense transcription in *Cryptococcus* only rarely results in the production of double-
891 stranded RNA. Dumesic and colleagues showed that delayed splicing is a source of siRNA
892 production in *C. neoformans* (DUMESIC *et al.* 2013). We thus anticipated that the absence of RNAi
893 would increase the level of intron retention. In agreement with previous reports in *C.*
894 *deneoformans*, we found that IR level was regulated by growth conditions in both *C. neoformans*
895 and *C. deuterogattii* (GONZALEZ-HILARION *et al.* 2016). However, the number of introns regulated by
896 IR was markedly larger in R265 suggesting that IR is better tolerated in this RNAi-deficient species.
897 We also expected that some compensatory mechanisms might be acting to control the level of IR
898 because IR rates were largely similar across the three species analyzed even though it was higher
899 in R265, at least at 37°C. It is important to note the remarkable effect of temperature on both IR
900 and antisense transcription, which might be related to a recent report that transposons are
901 specifically mobilized at this temperature in *C. deneoformans* (GUSA *et al.* 2020).
902 While most loci that have been lost in R265 compared to other *Cryptococcus* species
903 contain only a single gene, we also identified gene clusters that were missing in R265. Analysis of
904 the gene content within these clusters revealed a strong enrichment of genes coding for proteins
905 implicated in transport and transcriptional regulation. This finding was reminiscent of patterns
906 identified in metabolic gene clusters (MGCs) involved in primary metabolism, which typically
907 contain transcription factors and transporters (ROKAS *et al.* 2018). MGCs can be lost or gained in
908 fungi and several examples of instances of horizontal transfer of whole MGCs from one species to
909 another have been published (SLOT AND ROKAS 2010; ROKAS *et al.* 2018; WANG *et al.* 2019). In
910 filamentous fungi, the majority of MGCs are located within subtelomeric regions, which are largely

911 subjected to inter-chromosomal reshuffling (GLADIEUX *et al.* 2014). Two examples of lineage-
912 specific gene clusters harboring both transcription factors and transporters have been previously
913 reported in *C. neoformans* (RHODES *et al.* 2017), suggesting dynamic gene cluster gain and loss
914 events even with a single species in *Cryptococcus*. Interestingly, these *C. neoformans* lineage-
915 specific clusters also contain transcription factors and transporters (RHODES *et al.* 2017). A more
916 recent report suggests that genes within one of *these C. neoformans* clusters are co-regulated, as
917 is expected from a typical MGC (YU *et al.* 2020). In *Cryptococcus*, we found that the subtelomeric
918 regions were also enriched for characteristic MGC genes as well, and comparisons of subtelomeric
919 gene organization across the three *Cryptococcus* species suggested active reshuffling. This was in
920 agreement with previous data showing that subtelomeric genes are under strong evolutionary
921 pressure in *Cryptococcus* (DESJARDINS *et al.* 2017). We found a large number of genes encoding
922 transporters and TFs of unknown function in *Cryptococcus* subtelomeric regions. Surprisingly, most
923 of the TF genes identified in these MGCs within subtelomeric regions as well as in MGCs far from
924 telomeres were not annotated as TFs and were not included when a systematic TF deletion
925 collection was constructed and studied (JUNG *et al.* 2015). It therefore seems that the TF repertoire
926 in *Cryptococcus* may be larger than currently appreciated. Similarly, besides myo-inositol
927 transporters, which have been previously reported to be localized within subtelomeric regions
928 (XUE *et al.* 2010), the substrates of most transporters located in these regions remain unknown.
929 Genes within subtelomeric regions are silenced by H3K27me3 epigenetic marks and,
930 accordingly, are expressed at lower levels than genes located in more central regions of the
931 chromosomes. Similarly, genes within the subtelomeric clusters lost in R265 were poorly
932 expressed. Yet, their expression levels did not significantly change following deletion of the gene
933 encoding the H3K27me3 methyltransferase *EZH2,* suggesting they are either not regulated by
934 H3K27me3 or that additional changes are needed to activate expression of these genes like those
935 previously described in *Fusarium graminearum* (CONNOLLY *et al.* 2013). If this is the case, the

936 regulation of *GAL* genes by galactose might represent a good example of how genes within the
937 MGCs could be regulated in *Cryptococcus* (WICKES AND EDMAN 1995; MOYRAND *et al.* 2008; RUFF *et al.*
938 2009). Besides the *GAL* cluster, the function and regulation of most of MGC genes in *Cryptococcus*
939 are unknown. Nevertheless, our results suggest active exchange between subtelomeric regions
940 and more central parts of chromosomes in *Cryptococcus*, potentially reshaping primary
941 metabolism for adaptation to different environmental niches. They also emphasize how both
942 complete genome and precise annotations are needed to study these dynamics in fungi.
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958 **References**

959

960 Alcid, E. A. and T. Tsukiyama, 2016 Expansion of antisense lncRNA transcriptomes in budding yeast
961 species since the loss of RNAi. *Nature Structural and Molecular Biology* 23**:** 450-455.

962 Anders, S., P. T. Pyl and W. Huber, 2014 HTSeq—a Python framework to work with high-throughput
963 sequencing data. *Bioinformatics* 31**:** 166-169.

964 Basenko, E. Y., J. A. Pulman, A. Shanmugasundram, O. S. Harb, K. Crouch *et al.*, 2018 FungiDB: an
965 integrated bioinformatic resource for fungi and oomycetes. *Journal of Fungi* (Basel,
966 Switzerland) 4**:** 39.

967 Billmyre, R. B., S. Calo, M. Feretzaki, X. Wang and J. Heitman, 2013 RNAi function, diversity, and loss
968 in the fungal kingdom. *Chromosome Research* 21**:** 561-572.

969 Burke, J. E., A. D. Longhurst, P. Natarajan, B. Rao, J. Liu *et al.*, 2019 A non-Dicer RNase III and four
970 other novel factors required for RNAi-mediated transposon suppression in the human
971 pathogenic yeast *Cryptococcus neof*ormans. *G3* (Bethesda, Md.) 9**:** 2235-2244.

972 Cantarel, B. L., I. Korf, S. M. C. Robb, G. Parra, E. Ross *et al.*, 2008 MAKER: an easy-to-use annotation
973 pipeline designed for emerging model organism genomes. *Genome Research* 18**:** 188-196.

974 Carver, T., S. R. Harris, M. Berriman, J. Parkhill and J. A. McQuillan, 2012 Artemis: an integrated
975 platform for visualization and analysis of high-throughput sequence-based experimental
976 data. *Bioinformatics* 28.

977 Catania, S., P. A. Dumesic, H. Pimentel, A. Nasif, C. I. Stoddard *et al.*, 2020 Evolutionary persistence
978 of DNA methylation for millions of years after ancient loss of a *de novo* methyltransferase.
979 *Cell* 180**:** 263-277.e220.

980 Cheng, P.-Y., A. Sham and J. W. Kronstad, 2009 *Cryptococcus gattii* isolates from the British Columbia
981 cryptococcosis outbreak induce less protective inflammation in a murine model of infection
982 than *Cryptococcus neoformans*. *Infection and Immunity* 77**:** 4284.
983 Conesa, A., S. Götz, J. M. García-Gómez, J. Terol, M. Talón *et al.*, 2005 Blast2GO: a universal tool for
984 annotation, visualization and analysis in functional genomics research. *Bioinformatics* 21**:**
985 3674-3676.
986 Connolly, L. R., K. M. Smith and M. Freitag, 2013 The *Fusarium graminearum* histone H3 K27
987 methyltransferase KMT6 regulates development and expression of secondary metabolite
988 gene clusters. *PLOS Genetics* 9**:** e1003916.
989 D'Souza, C. A., J. W. Kronstad, G. Taylor, R. Warren, M. Yuen *et al.*, 2011 Genome variation in
990 *Cryptococcus gattii*, an emerging pathogen of immunocompetent hosts. *mBio* 2**:** e00342-
991 00310.
992 Dal Molin, A., A. Minio, F. Griggio, M. Delledonne, A. Infantino *et al.*, 2018 The genome assembly of
993 the fungal pathogen *Pyrenochaeta lycopersici* from Single-Molecule Real-Time sequencing
994 sheds new light on its biological complexity. *PLOS One* 13**:** e0200217.
995 Desjardins, C. A., C. Giamberardino, S. M. Sykes, C.-H. Yu, J. L. Tenor *et al.*, 2017 Population genomics
996 and the evolution of virulence in the fungal pathogen Cryptococcus neoformans. *Genome*
997 *research* 27**:** 1207-1219.
998 Ding, C., Yin, J., Tovar, E.M.M., Fitzpatrick, D.A., Higgins, D.G. and Thiele, D.J. (2011) The copper
999 regulon of the human fungal pathogen *Cryptococcus neoformans* H99. *Mol Microbiol*, **81**,
1000 1560-1576.
1001 Dumesic, Phillip A., Christina M. Homer, James J. Moresco, Lindsey R. Pack, Erin K. Shanle *et al.*,
1002 2015 Product binding enforces the genomic specificity of a yeast polycomb repressive
1003 complex. *Cell* 160**:** 204-218.

1004 Dumesic, P. A., P. Natarajan, C. Chen, I. A. Drinnenberg, B. J. Schiller *et al.*, 2013 Stalled spliceosomes
1005 are a signal for RNAi-mediated genome defense. *Cell* 152**:** 957-968.
1006 Dunn, N. A., D. R. Unni, C. Diesh, M. Munoz-Torres, N. L. Harris *et al.*, 2019 Apollo: Democratizing
1007 genome annotation. *PLOS Computational Biology* 15**:** e1006790.
1008 Farrer, R. A., C. A. Desjardins, S. Sakthikumar, S. Gujja, S. Saif *et al.*, 2015 Genome evolution and
1009 innovation across the four major lineages of *Cryptococcus gattii*. *mBio* 6**:** e00868-00815.
1010 Farrer, R.A., M. Chang, M.J. Davis, L. van Dorp, D. Yang *et al*., 2019. A new lineage of *Cryptococcus*
1011 *gattii* (VGV) discovered in the Central Zambezian Miombo Woodlands. *mBio* 10:e02306-19.
1012 Feretzaki, M., R. B. Billmyre, S. A. Clancey, X. Wang and J. Heitman, 2016 Gene network
1013 polymorphism illuminates loss and retention of novel RNAi silencing components in the
1014 *Cryptococcus* pathogenic species complex. *PLOS Genetics* 12**:** e1005868-e1005868.
1015 Ferrareze, P. A. G., R. S. A. Streit, P. R. dos Santos, F. M. dos Santos, R. M. C. de Almeida *et al.*, 2017
1016 Transcriptional analysis allows genome reannotation and reveals that *Cryptococcus gattii*
1017 VGII undergoes nutrient restriction during Infection. *Microorganisms* 5**:** 49.
1018 Fraser, J. A., J. C. Huang, R. Pukkila-Worley, J. A. Alspaugh, T. G. Mitchell *et al.*, 2005 Chromosomal
1019 translocation and segmental duplication in *Cryptococcus neoformans*. *Eukaryotic Cell* 4**:** 401-
1020 406.
1021 Giordano, F., L. Aigrain, M. A. Quail, P. Coupland, J. K. Bonfield *et al.*, 2017 *De novo* yeast genome
1022 assemblies from MinION, PacBio and MiSeq platforms. *Scientific Reports* 7**:** 3935.
1023 Gladieux, P., J. Ropars, H. Badouin, A. Branca, G. Aguileta *et al.*, 2014 Fungal evolutionary genomics
1024 provides insight into the mechanisms of adaptive divergence in eukaryotes. *Molecular*
1025 *Ecology* 23**:** 753-773.
1026 Gonzalez-Hilarion, S., D. Paulet, K.-T. Lee, C.-C. Hon, P. Lechat *et al.*, 2016 Intron retention-
1027 dependent gene regulation in *Cryptococcus neoformans*. *Scientific Reports* 6**:** 32252.

1028 Grabherr, M. G., B. J. Haas, M. Yassour, J. Z. Levin, D. A. Thompson *et al.*, 2011 Full-length
1029 transcriptome assembly from RNA-seq data without a reference genome. *Nature*
1030 *Biotechnology* 29**:** 644-652.
1031 Gusa, A., J. D. Williams, J.-E. Cho, A. F. Averette, S. Sun *et al.*, 2020 Transposon mobilization in the
1032 human fungal pathogen *Cryptococcus* is mutagenic during infection and promotes drug
1033 resistance in vitro. *Proceedings of the National Academy of Sciences of the USA* 117**:** 9973.
1034 Haas, B. J., Q. Zeng, M. D. Pearson, C. A. Cuomo and J. R. Wortman, 2011 Approaches to fungal
1035 genome annotation. *Mycology* 2**:** 118-141.
1036 Hagen, F., K. Khayhan, B. Theelen, A. Kolecka, I. Polacheck *et al.*, 2015 Recognition of seven species
1037 in the *Cryptococcus gattii*/*Cryptococcus neoformans* species complex. *Fungal Genetics and*
1038 *Biology* 78**:** 16-48.
1039 Haridas, S., A. Salamov and I. V. Grigoriev, 2018 Fungal Genome Annotation, pp. 171-184 in *Fungal*
1040 *Genomics: Methods and Protocols*, edited by R. P. de Vries, A. Tsang and I. V. Grigoriev.
1041 Springer New York, New York, NY.
1042 Hoff, K. J., S. Lange, A. Lomsadze, M. Borodovsky and M. Stanke, 2016 BRAKER1: unsupervised RNA-
1043 seq-based genome annotation with GeneMark-ET and AUGUSTUS. *Bioinformatics* (Oxford,
1044 England) 32**:** 767-769.
1045 Huang, M., Hebert, A.S., Coon, J.J. and Hull, C.M. (2015) Protein composition of infectious spores
1046 reveals novel sexual development and germination factors in *Cryptococcus*. *PLoS Genet*, **11**,
1047 e1005490-e1005490.
1048 Huston, S. M., S. S. Li, D. Stack, M. Timm-McCann, G. J. Jones *et al.*, 2013 *Cryptococcus gattii* is killed
1049 by dendritic cells, but evades adaptive immunity by failing to induce dendritic cell
1050 maturation. *The Journal of Immunology* 191**:** 249.
1051 James, T. Y., J. E. Stajich, C. T. Hittinger and A. Rokas, 2020 Toward a fully resolved fungal tree of life.
1052 *Annual Review of Microbiology* 74.

1053 Janbon, G., 2018 Introns in *Cryptococcus*. *Memorias do Instituto Oswaldo Cruz* 113**:** e170519-
1054 e170519.
1055 Janbon, G., S. Y. Maeng, D-F., Y.-J. Ko, K.-W. Jung, F. Moyrand *et al.*, 2010 Characterizing the role of
1056 RNA silencing components in *Cryptococcus neoformans*. *Fungal Genetics and Biology* 47**:**
1057 1070-1080.
1058 Janbon, G., K. L. Ormerod, D. Paulet, E. J. Byrnes III, G. Chatterjee *et al.*, 2014 Analysis of the genome
1059 and transcriptome of *Cryptococcus neoformans* var. *grubii* reveals complex RNA expression
1060 and microevolution leading to virulence attenuation. *PLOS Genetics* 10**:** e1004261.
1061 Jung, K.-W., D.-H. Yang, S. Maeng, K.-T. Lee, Y.-S. So *et al.*, 2015 Systematic functional profiling of
1062 transcription factor networks in *Cryptococcus neoformans*. *Nature Communications* 6**:** 6757.
1063 Kidd, S. E., F. Hagen, R. L. Tscharke, M. Huynh, K. H. Bartlett *et al.*, 2004 A rare genotype of
1064 *Cryptococcus gattii* caused the cryptococcosis outbreak on Vancouver Island (British
1065 Columbia, Canada). *Proceeding of the National Academy of Sciences of the USA* 101**:** 17258-
1066 17263.
1067 Kim, D., G. Pertea, C. Trapnell, H. Pimentel, R. Kelley *et al.*, 2013 TopHat2: accurate alignment of
1068 transcriptomes in the presence of insertions, deletions and gene fusions. *Genome biology*
1069 14**:** R36-R36.
1070 Kwon-Chung, K. J., J. A. Fraser, T. L. Doering, Z. Wang, G. Janbon *et al.*, 2014 *Cryptococcus*
1071 *neoformans* and *Cryptococcus gattii*, the etiologic agents of cryptococcosis. *Cold Spring*
1072 *Harbor Perspectives in Medicine* 4**:** a019760.
1073 Lam, W. C., R. Upadhya, C. A. Specht, A. E. Ragsdale, C. R. Hole *et al.*, 2019 Chitosan biosynthesis
1074 and virulence in the human fungal pathogen *Cryptococcus gattii*. *mSphere* 4**:** e00644-00619.
1075 Langmead, B., and S. L. Salzberg, 2012 Fast gapped-read alignment with Bowtie 2. *Nature Methods*
1076 9**:** 357-359.

1077 Lee, K.-T., So, Y.-S., Yang, D.-H., Jung, K.-W., Choi, J., *et al.* (2016) Systematic functional analysis of
1078 kinases in the fungal pathogen *Cryptococcus neoformans*. *Nature Communications*, **7**, 12766.
1079 Lomsadze, A., P. D. Burns and M. Borodovsky, 2014 Integration of mapped RNA-seq reads into
1080 automatic training of eukaryotic gene finding algorithm. *Nucleic Acids Research* 42**:** e119-
1081 e119.
1082 Lowe, T. M., and P. P. Chan, 2016 tRNAscan-SE On-line: integrating search and context for analysis
1083 of transfer RNA genes*. Nucleic Acids Research* 44**:** W54-W57.
1084 Ma, H., F. Hagen, D. J. Stekel, S. A. Johnston, E. Sionov *et al.*, 2009 The fatal fungal outbreak on
1085 Vancouver Island in characterized by enhanced intracellular parasitism driven by
1086 mitochondrial regulation. *Proceeding of the National Academy of Sciences of the USA* 106**:**
1087 12980-12985.
1088 Martin, M., 2011 Cutadapt removes adapter sequences from high-throughput sequencing reads.
1089 EMBnet.journal; Vol 17, No 1: Next Generation Sequencing Data Analysis.
1090 Min, B., I. V. Grigoriev and I.-G. Choi, 2017 FunGAP: Fungal Genome Annotation Pipeline using
1091 evidence-based gene model evaluation. *Bioinformatics* 33**:** 2936-2937.
1092 Moyrand, F., I. Lafontaine, T. Fontaine and G. Janbon, 2008 *UGE1* and *UGE2* regulate the UDP-
1093 glucose/UDP-galactose equilibrium in *Cryptococcus neoformans*. *Eukaryotic Cell* 7**:** 2069-
1094 2077.
1095 Mudge, J. M., and J. Harrow, 2016 The state of play in higher eukaryote gene annotation. *Nature*
1096 *Reviews Genetics* 17**:** 758-772.
1097 Ngamskulrungroj, P., Y. Chang, E. Sionov and K. J. Kwon-Chung, 2012 The primary target organ of
1098 *Cryptococcus gattii* Is different from that of *Cryptococcus neoformans* in a murine model.
1099 *mBio* 3**:** e00103-00112.
1100 Pertea, G., and M. Pertea, 2020 GFF Utilities: GffRead and GffCompare. *F1000Research* 9**:** 304.

1101 Priebe, S., C. Kreisel, F. Horn, R. Guthke and J. Linde, 2014 FungiFun2: a comprehensive online
1102 resource for systematic analysis of gene lists from fungal species. *Bioinformatics* 31**:** 445-
1103 446.
1104 Rhodes, J., C. A. Desjardins, S. M. Sykes, M. A. Beale, M. Vanhove *et al.*, 2017 Tracing genetic
1105 exchange and biogeography of *Cryptococcus neoformans* var. *grubii* at the global population
1106 level. *Genetics***:** 10.1534/genetics.1117.203836.
1107 Rokas, A., J. H. Wisecaver and A. L. Lind, 2018 The birth, evolution and death of metabolic gene
1108 clusters in fungi. *Nature Reviews Microbiology* 16**:** 731-744.
1109 Ruff, J. A., J. K. Lodge and L. G. Baker, 2009 Three galactose inducible promoters for use in *C.*
1110 *neoformans* var. *grubii*. *Fungal Genetics and Biology* 46**:** 9-16.
1111 Semighini C.P., A.F. Averette, J.R. Perfect, and J. Heitman, 2011. Deletion of *Cryptococcus*
1112 *neoformans* AIF ortholog promotes chromosome aneuploidy and fluconazole-resistance in
1113 a metacaspase-independent manner. *PLOS Pathogens* 7: e1002364.
1114 Sharpe, D. 2015 Chi-Square Test is Statistically Significant: Now What?, Practical Assessment.
1115 *Research, and Evaluation*: Vol. 20 , Article 8. DOI: https://doi.org/10.7275/tbfa-x148.
1116 Shen, X.-X., D. A. Opulente, J. Kominek, X. Zhou, J. L. Steenwyk *et al.*, 2018 Tempo and mode of
1117 genome evolution in the budding yeast subphylum. *Cell* 175**:** 1533-1545.e1520.
1118 Slater, G. S., and E. Birney, 2005 Automated generation of heuristics for biological sequence
1119 comparison. *BMC Bioinformatics***:** 31.
1120 Slot, J. C., and A. Rokas, 2010 Multiple *GAL* pathway gene clusters evolved independently and by
1121 different mechanisms in fungi. *Proceeding of the National Academy of Sciences of the USA*
1122 107**:** 10136-10141.
1123 Stanke, M., M. Diekhans, R. Baertsch and D. Haussler, 2008 Using native and syntenically mapped
1124 cDNA alignments to improve *de novo* gene finding. *Bioinformatics* 24**:** 637-644.

1125 Testa, A. C., J. K. Hane, S. R. Ellwood and R. P. Oliver, 2015 CodingQuarry: highly accurate hidden
1126 Markov model gene prediction in fungal genomes using RNA-seq transcripts. *BMC Genomics*
1127 16**:** 170.
1128 Törönen, P., A. Medlar and L. Holm, 2018 PANNZER2: a rapid functional annotation web server.
1129 *Nucleic Acids Research* 46**:** W84-W88.
1130 Trapnell, C., B. A. Williams, G. Pertea, A. Mortazavi, G. Kwan *et al.*, 2010 Transcript assembly and
1131 quantification by RNA-seq reveals unannotated transcripts and isoform switching during cell
1132 differentiation. Nature Biotechnology 28**:** 511-515.
1133 Tutar, Y., 2012 Pseudogenes. *Comparative and Functional Genomics* 2012**:** 424526-424526.
1134 Wallace, E. W. J., C. Maufrais, J. Sales-Lee, L. R. Tuck, L. de Oliveira *et al.*, 2020 Quantitative global
1135 studies reveal differential translational control by start codon context across the fungal
1136 kingdom. *Nucleic Acids Research* 48**:** 2312-2331.
1137 Wang, M., H. Fu and R. Ruan, 2019 A small horizontally transferred gene cluster contributes to the
1138 sporulation of *Alternaria alternata*. *Genome Biology and Evolution* 11**:** 3436-3444.
1139 Wang, X., Y. P. Hsueh, W. Li, A. Floyd, R. Skalsky *et al.*, 2010 Sex-induced silencing defends the
1140 genome of *Cryptococcus neoformans* via RNAi. *Genes & Development* 24**:** 2566-2582.
1141 Wickes, B. L., and J. C. Edman, 1995 The *Cryptococcus neoformans GAL7* gene and its use as an
1142 inducible promoter. *Molecular Microbiology* 16**:** 1099-1109.
1143 Wilm, A., D. G. Higgins, F. Valentin, G. Blackshields, H. McWilliam *et al.*, 2007 Clustal W and Clustal
1144 X version 2.0. *Bioinformatics* 23**:** 2947-2948.
1145 Xue, C., T. Liu, L. Chen, W. Li, I. Liu *et al.*, 2010 Role of an expanded inositol transporter repertoire
1146 in *Cryptococcus neoformans* sexual reproduction and virulence. *mBio* 1**:** e00084-00010.
1147 Yadav, V., S. Sun, R. B. Billmyre, B. C. Thimmappa, T. Shea *et al.*, 2018 RNAi is a critical determinant
1148 of centromere evolution in closely related fungi. *Proceeding of the National Academy of*
1149 *Sciences of the USA* 115**:** 3108.

1150 Yu, C.-H., Y. Chen, C. A. Desjardins, J. L. Tenor, D. L. Toffaletti *et al.*, 2020 Landscape of gene
1151 expression variation of natural isolates of Cryptococcus neoformans in response to
1152 biologically relevant stresses. *Microbial Genomics* 6.
1153 Zhu, P., B. Zhai, X. Lin, and A. Idnurm, 2013. Congenic strains for genetic analysis of virulence traits
1154 in *Cryptococcus gattii*. *Infection and Immunity* 81: 2616-2625.
1155
1156