

# Complex regulatory role of DNA methylation in caste- and age-specific expression of a termite.

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## Abstract

The reproductive castes of eusocial insects are often characterised by extreme lifespans and reproductive output, indicating an absence of the fecundity/longevity trade-off. The role of DNA methylation in the regulation of caste- and age-specific gene expression in eusocial insects is controversial. While some studies find a clear link to caste formation in honeybees and ants, others find no correlation when replication is increased across independent colonies. Although recent studies have identified transcription patterns involved in the maintenance of high reproduction throughout the long lives of queens, the role of DNA methylation in the regulation of these genes is unknown. We carried out a comparative analysis of DNA methylation in the regulation of caste-specific transcription and its importance for the regulation of fertility and longevity in queens of the higher termite, *Macrotermes natalensis*. We found evidence for significant, well-regulated changes in DNA methylation in mature compared to young queens, especially in several genes related to ageing and fecundity in mature queens. We also found a strong link between methylation and caste-specific alternative splicing. This study reveals a complex regulatory role of fat body DNA methylation both in the division of labour in termites, and during the reproductive maturation of queens.

## 1 Introduction

2 DNA methylation, the epigenetic modification of DNA, is widespread among eukaryotes and  
3 is known to be important for transcriptional regulation of genes and repression of transposable  
4 elements (Zemach *et al.*, 2010). Age-related changes in DNA methylation levels and an increased  
5 variability known as epigenetic drift have been recognised as an important hallmark of ageing in  
6 mammals (Issa *et al.*, 2014; López-Otín *et al.*, 2013). DNA methylation has garnered consider-  
7 able attention within social insects with an apparent role in the regulation of sterile and fertile  
8 castes in honey bees (Lyko *et al.*, 2010) and in ants (Bonasio *et al.*, 2012). A more recent study  
9 found a significant role of methylation in the task division of worker bees (de Souza Araujo  
10 and Arias, 2021). However, there remains considerable debate surrounding the universality of  
11 the role of DNA methylation in the transcriptional regulation of caste-specific genes in eusocial  
12 insects (Herb *et al.*, 2012; Patalano *et al.*, 2015; Libbrecht *et al.*, 2016). In bumble bees, DNA  
13 methylation appears to be more important for worker reproduction (Amarasinghe *et al.*, 2014)  
14 than for caste differentiation (Marshall *et al.*, 2019). Two studies found no influence of DNA

methylation on the formation of behavioural castes in a wasp (Patalano *et al.*, 2015) and an ant (Patalano *et al.*, 2015; Libbrecht *et al.*, 2016) that live in simple societies. In fact, the authors of the latter study claimed previous evidence for the role of DNA methylation in the division of labour was weak and that further studies required more robust methodology, especially greater replication (Libbrecht *et al.*, 2016). Most of these studies have concentrated on social Hymenoptera (ants, bees and wasps), with the exception of two studies on the role of DNA methylation in the division of labour in adult termites. The first of these studies investigated whole-body methylation patterns for the lower, drywood termite *Zootermopsis nevadensis* (Glastad *et al.*, 2016), which forms simple colonies, in which workers retain the possibility to become fertile (Weil *et al.*, 2007). In the second study, head methylomes of the subterranean termite, *Reticulitermes speratus*, were investigated, a species with an intermediate level of social complexity (Shigenobu *et al.*, 2022). While the first study found large differences between castes in *Z. nevadensis* (Glastad *et al.*, 2016), Shigenobu *et al.* (2022) found very strong correlations in DNA methylation patterns between castes of *R. speratus*. However, in the first study, limited replication was performed within one single colony, while in the second study non-replicated castes were sampled from different colonies, so that the effect of colony-specific variation, inherent in previous studies (Libbrecht *et al.*, 2016), could not be excluded in either of these studies. The general role of DNA methylation in the transcriptional regulation of termite castes is therefore still unclear, especially in higher termites that form complex colonies with lifelong sterile worker castes.

Beside reproductive division of labour, the eusocial insects are also characterised by extreme longevity among fertile castes, indicating an apparent absence of the fecundity-longevity trade-off attributed to non-social insects (Korb *et al.*, 2021). Several, recent studies have presented evidence for the transcriptional regulation of specific gene co-expression modules associated with old but highly fertile queens in ants (Harrison *et al.*, 2021), bees (Séguret *et al.*, 2021) and termites (Lin *et al.*, 2021; Séité *et al.*, 2022). However, the role of DNA methylation in this absence of the longevity-fecundity trade-off in eusocial insects is so far unknown.

In this study, we investigated caste- and age-specific DNA methylation profiles to make inferences on the regulation of genes important for the extreme longevity and high fecundity of reproductives in the higher termite, *Macrotermes natalensis*. This foraging, fungus-farming ter-

45 mite is characterised by large colonies and sterile workers. Kings and queens can live for over 20  
46 years (Keller, 1998), with the highly fertile queen laying thousands of eggs per day (Kaib *et al.*,  
47 2001). The mature *Macrotermes* queens are characterised by a hypertrophic abdomen, as well  
48 as several further metabolic and physiological differences compared to virgin queens, such as  
49 enlarged corpora allata (Sieber and Leuthold, 1982), increased DNA content and major changes  
50 in insulin signalling and fat storage (Séité *et al.*, 2022).

51 We carried out reduced representation bisulfite sequencing (RRBS) on four phenotypes (short-  
52 lived, sterile female workers, young virgin queens, 20-year-old queens, and 20-year-old kings),  
53 replicated across three independent colonies from this higher termite and related DNA methy-  
54 lation patterns to caste- and age-specific gene expression. This was performed on the fat body,  
55 since we recently showed the importance of this tissue for the long reproductive life of the  
56 reproductive termite castes (Séité *et al.*, 2022).

## 57 Results and Discussion

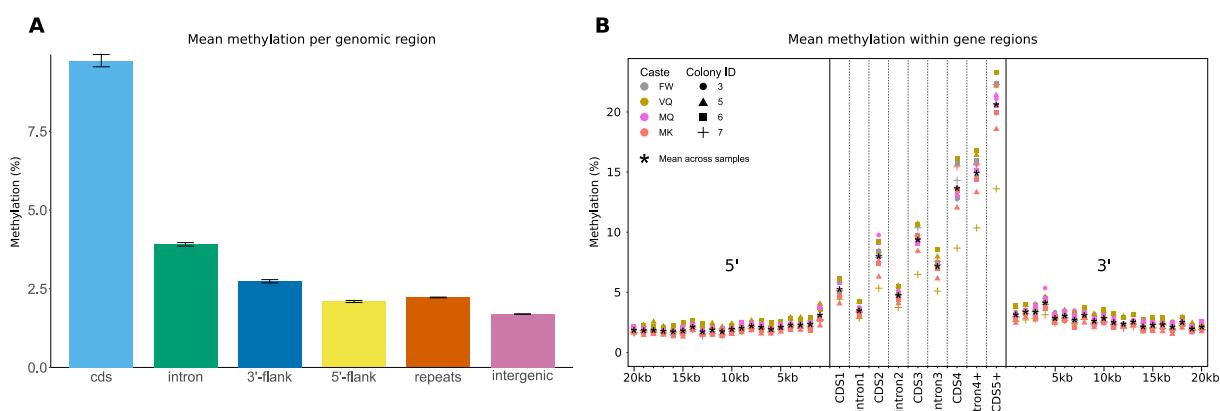
### 58 RRBS is a robust method for determining genomic methylation patterns in termites

59 For each of the four phenotypes, female workers (FW), virgin queens (VQ), mature queens  
60 (MQ) and mature kings (MK), we aimed to produce reduced representation bisulfite sequencing  
61 (RRBS) for 3 replicates from independent colonies. An accurate estimation of methylation levels  
62 relies heavily on an efficient conversion rate of unmethylated sites with the bisulfite treatment.  
63 To measure the erroneous, non-conversion rates, each sample was supplemented with a non-  
64 methylated lambda spike-in control (see methods). We kept only those samples with a non-  
65 conversion rate lower than 2% (Table S1). We generated between 32.1M and 61.4M bisulfite  
66 treated reads per sample (Table S1). These reads were mapped to the genome (mapping rate:  
67 67.3%-71.2%; Table S1) to quantify methylation levels, and for each sample only CpGs to which  
68 at least 5 reads mapped were included in analyses. We were able to quantify methylation levels  
69 (at least 5 reads) of 6.29 million CpG sites (19.1% of all genomic CpGs). For each phenotype  
70 most CpGs were sequenced for all 3 replicates, ranging from 2.8M to 3.6M CpGs per phenotype  
71 (Fig. S1A-D). In support for the reliability of the RRBS method, a large proportion of the CpGs  
72 (1.97M, 31.3%) were sequenced consistently within all 12 samples (4 phenotypes x 3 replicates),

73 which was by far the largest intersection of the 12 sets of sequenced CpGs (Fig. S1E). All  
74 subsequent analyses are based on this subset of 1.97M CpGs.

75 *High gene body methylation*

76 Within the subset of 1.97M CpGs that were sequenced within all 12 individuals, we found de-  
77 tectable methylation at 49.0% (FDR corrected binomial p-value < 0.05, based on non-conversion  
78 rate) of sites in at least one sample. For each of the 12 samples, methylation level was calcu-  
79 lated for each sequenced CpG as the proportion of mapped reads that were putatively methylated  
80 (non-converted cytosines). To estimate overall genomic methylation levels, we calculated means  
81 across the 12 samples at each CpG. Methylation levels varied throughout the genome, with high-  
82 est rates within coding regions (mean 9.74% per CpG, standard error: 0.20) and lowest rates  
83 within intergenic regions (mean: 1.70%, SE: 0.01; Fig. 1A). In repetitive regions, methylation  
84 was higher than in intergenic regions (mean: 2.22%, SE: 0.01), indicating that transposable  
85 elements (TEs) may be targeted by DNA methylation. Similar to findings for the lower termite,  
86 *Z. nevadensis* (Glastad *et al.*, 2016), methylation was relatively high in introns (mean: 3.91%,  
87 SE: 0.05 Fig. 1). In support of findings for *Z. nevadensis* (Glastad *et al.*, 2016) but in contrast  
88 to Hymenoptera (Bonasio *et al.*, 2012; Patalano *et al.*, 2015), we found that, for all samples,  
89 methylation levels increased along the gene body, with highest levels at 3' exons (13.6-23.3%  
90 among 5th to last exons) and introns (10.4-16.8% among 4th to last introns; Fig. 1B), suggesting  
91 this gene body methylation pattern may be widespread among termites.



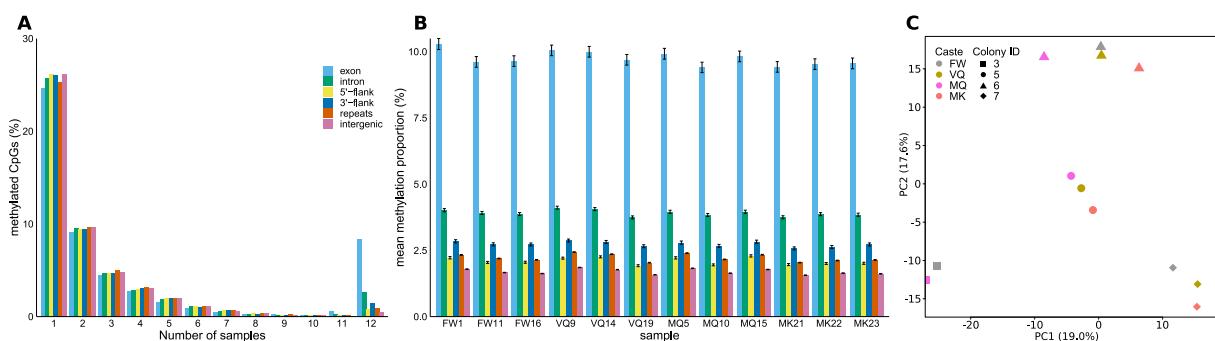
**Figure 1:** Genomic variation in methylation. In **A.** mean methylation proportions among all 12 samples are shown for 6 categories of genome regions. Error bars are standard error. Flanks are defined as 10kb up- or downstream of coding regions. **B.** Mean methylation (%) within gene bodies (exons and introns) and in twenty 1kb bins at 5'- and 3'-flanking regions of genes. Each dot represents mean methylation for one of twelve samples across all sequenced CpGs within the region of interest. The four phenotypes (FW, VQ, MQ, MK) are represented by colour; the colonies, from which replicates originated, are represented by shape. Stars show means across all 12 samples.

92 *Greater variation in methylation between colonies than between phenotypes*

93 We detected high individual variation in methylation patterns, with 24.7% to 26.2% of CpGs  
94 methylated in only 1 of the 12 samples, while only 9.1% to 9.7% were methylated in 2 individu-  
95 als. Interestingly, as previously found in the clonal raider ant, *Dinoponera quadriceps* (Libbrecht  
96 *et al.*, 2016), we found a substantial number of CpGs (8.4%) within coding sequence and in-  
97 trons (2.7%) that were robustly methylated within all 12 samples (Fig. 2A). These robustly  
98 methylated CpGs were situated in genes enriched for GO-terms related to cell differentiation,  
99 cell adhesion and regulation of cellular processes (Table S2). Interestingly, robustly methylated  
100 genes (containing at least one CpG methylated in all 12 samples) were more frequently differ-  
101 entially expressed between phenotypes (89.6%), compared to other genes (64.9%), suggesting  
102 an important role of DNA methylation in the regulation of gene transcription. Furthermore,  
103 methylation patterns (proportion of methylated reads per CpG), correlated strongly and uni-  
104 formly between all samples (Pearson's  $r$ : 0.600-0.781;  $p$ -value = 0), especially within coding  
105 sequence (0.889-0.960), indicating little differentiation between castes, similar to findings for the  
106 subterranean termite, *R. speratus* (Shigenobu *et al.*, 2022). The slightly lower correlations we  
107 report here compared to those found for *R. speratus* may be linked to a number of differences in

108 this current study, such as colony replication, RRBS rather than whole genome BS-sequencing,  
109 or may be related to species-specific patterns. Furthermore, the high correlations we found be-  
110 tween VQ and MQ (0.663-0.778) suggest DNA methylation patterns are well maintained with  
111 age in termite queens. This apparent lack of epigenetic drift, at least for DNA methylation, may  
112 help to explain the recently documented, well-regulated transcription of anti-ageing genes in *M.*  
113 *natalensis* queens (Séité *et al.*, 2022).

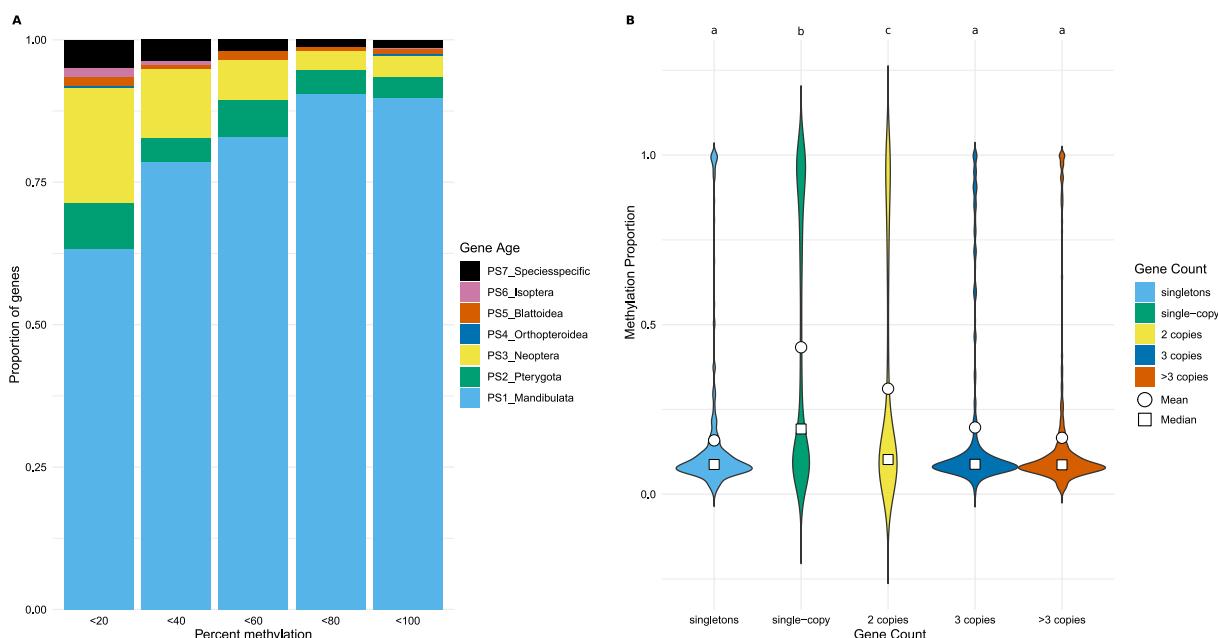
114 Methylation levels (proportion of methylated reads) also varied among individuals, with coding  
115 methylation ranging from mean 9.41% ( $\pm$  0.20 standard error) in the mature queen from colony  
116 5 (sample ID: MQ10) to 10.29% ( $\pm$  0.21 SE) in the female worker sample from colony 3 (FW1;  
117 Fig. 2B). Intergenic CpGs, on the other hand, were most highly methylated in the VQ sample  
118 from colony 5 (VQ9; mean: 1.85%  $\pm$  0.01 SE) and lowest in the MK sample from colony 5  
119 (MK21; mean: 1.56%  $\pm$  0.01 SE). A principal component analysis revealed that methylation  
120 patterns vary more between colonies than between castes (Fig. 2C) as previously found for the  
121 ants, *Cerapachys biroi* (Libbrecht *et al.*, 2016) and *Dinoponera quadriceps*, and the paper wasp,  
122 *Polistes canadensis* (Patalano *et al.*, 2015). This highlights the importance of replication across  
123 independent colonies in methylation studies as previously reported (Libbrecht *et al.*, 2016), thus  
124 raising the question of whether caste-specific methylation patterns detected within a single colony  
125 for the lower termite *Z. nevadensis* were species- or colony-specific (Glastad *et al.*, 2016). High  
126 colony variation is confirmed by a 3-way ANOVA among the 10 000 most variable sites, in which  
127 colony ( $F(3,1.20 \times 10^5) = 843.2$ ,  $p = 0.0$ ) has an effect size (generalised eta squared[ges]=0.021)  
128 larger than that of phenotype ( $F(3,1.20 \times 10^5) = 492.1$ ,  $p = 7.70 \times 10^{-318}$ , ges=0.012), while genomic  
129 region (exon, intron, 5'-flank, 3'-flank, repeats, intergenic) was an even stronger predictor of  
130 methylation level ( $F(5,1.20 \times 10^5) = 720.0$ ,  $p = 0$ , ges = 0.029). However, significant interactions  
131 existed between all three factors, indicating differing effects of each combination of phenotype,  
132 colony membership and genomic region on methylation level.



**Figure 2:** Individual variation in methylation. **A.** Proportions of CpGs that are methylated (FDR < 0.05) in varying numbers of 12 samples within 6 genomic regions. **B.** Mean proportions of methylated reads across all CpGs for each of the 12 samples (4 phenotypes x 3 replicates). **C.** Principal component analysis of methylation at 1000 most variable CpGs in 12 samples, spanning four phenotypes, represented by colour (FW, VQ, MQ and MK), from four colonies, represented by shape. The first two principal components are displayed on the x- and y-axes with variance explained in brackets.

133 *Conserved, single-copy genes are more highly methylated*

134 We performed two analyses which confirmed higher methylation levels for conserved genes. We  
135 first analysed gene age by determining the broadest phylogenetic taxon for which a gene ortholog  
136 could be found, ranging from species-specific to Mandibulata. The proportion of highly con-  
137 served genes, found in the oldest category, Mandibulata, was highest among genes with methy-  
138 lation levels greater than 80%, while species-specific genes were proportionally most abundant  
139 among lowly methylated genes (Fig. 3A). In further support for greater methylation of conserved  
140 genes, we found significantly higher methylation levels among single-copy ortholog genes (single  
141 copy in *M. natalensis* with orthology in other insects) than in multi-copy genes (> 2 paralogs).  
142 Similarly, for singletons (single-copy, species-specific genes), which are likely evolutionarily novel  
143 compared to orthologs, methylation levels were lower than in single-copy orthologs and did not  
144 differ from multi-copy genes. The methylation of 2-copy genes were intermediate between single-  
145 copy and multi-copy genes (Fig. 3B).

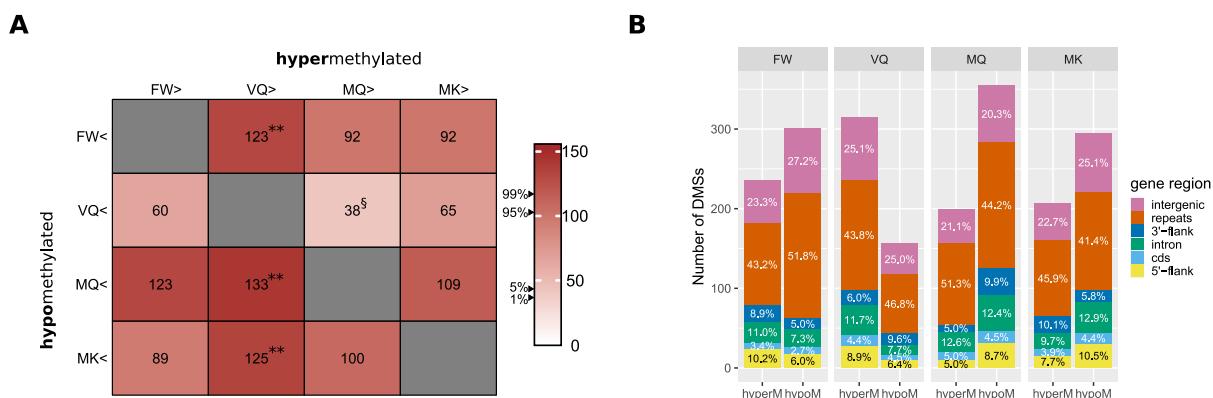


**Figure 3:** Methylation and gene conservation. A. Proportions of gene age categories within 5 categories of methylation level. B. Methylation level within genes with varying numbers of copies. Singleton = no paralogs or orthologs; single-copy = no paralogs but with orthologs in other species; other gene groups have varying numbers of paralogs.

146 *Ageing and fertility genes hypomethylated in mature queens*

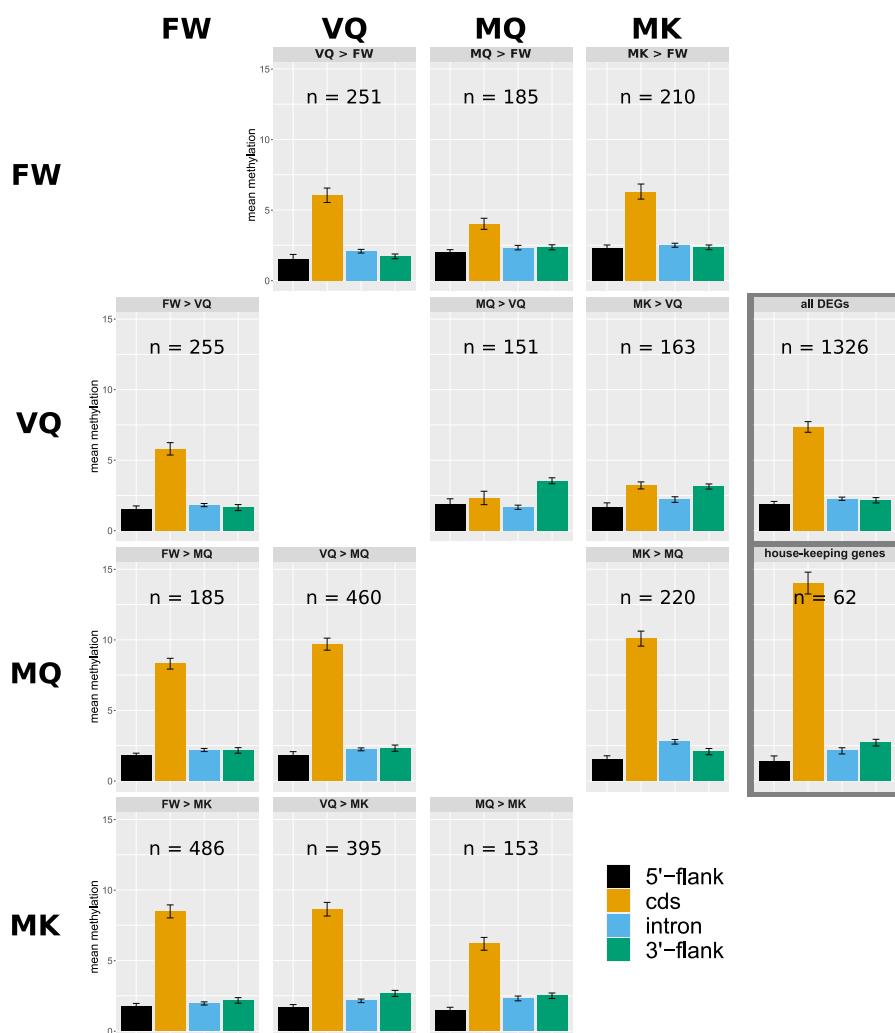
147 Despite the larger variation between colonies, we found 1344 CpG sites to be significantly differ-  
148 entially methylated (DMS) between phenotypes. We tested whether these numbers of DMS are  
149 greater or smaller than can be expected between two groups of three randomly assigned samples  
150 (1000 bootstraps; 95% confidence interval: [45-102]; 99% confidence interval: [40-114]). In this  
151 manner, we found a significant number of DMS that were hypermethylated in VQ compared to  
152 each of the other castes (> 95%). In MQ, on the other hand, there were significant numbers  
153 of DMS that were hypomethylated compared to other castes (> 95%; Fig. 4A). The num-  
154 bers of unique DMS varied among phenotypes and genomic regions, and were enriched within  
155 coding regions (2.7-5.0%) compared to the proportion of total sequenced CpGs within coding  
156 regions (1.2%). Interestingly, the largest category of DMS were those hypomethylated in MQ  
157 (365 unique sites) while the smallest category contained sites hypomethylated in VQ (163) (Fig.  
158 4B). Of the 1291 DMS, 386 lay within 261 genes (DMGs), of which 111 genes contained sites

159 hypomethylated in MQ, while 87 genes contained sites hypermethylated in VQ. These striking  
 160 results indicate a major shift in methylation patterns occurs during queen maturation for a  
 161 subset of genes.



**Figure 4:** Differentially methylated sites. **A.** Numbers of CpG sites hyper- (columns) and hypomethylated (rows) between pairs of phenotypes. Bootstrapping was carried out based on numbers of significant sites in 1000 comparisons between randomised 3x3 samples; 95% confidence interval: [45-102]; 99% confidence interval: [40-114]. \*\*  $> 0.99$ ; \*  $> 0.95$ ; §  $< 0.05$ . **B.** Proportions of DMSs per genomic region for each phenotype. Unique DMSs were counted from all pairwise comparisons between the four phenotypes.

162 Several of the genes with significantly decreased methylation in MQ compared to VQ have  
 163 important roles in ageing, including 2 regulators of Notch signalling, 2 genes involved in Wnt  
 164 signalling, a Sirtuin, a sphingomyelinase, important for cellular stress, and a gene responsible  
 165 for the regulation of misfolded proteins (Table S3). Further genes are related to fertility such  
 166 as Vitellogenin and an ecdysone receptor (Table S3). In a previous study on this species, the  
 167 major importance of insulin signalling in the fat body during the maturation process of queens  
 168 was highlighted (Séité *et al.*, 2022). It is therefore striking that *chico*, the substrate of insulin  
 169 receptors in the insulin signalling pathway, and *daw*, with known functions in insulin regulation,  
 170 are hypomethylated and differentially expressed in MQ compared to VQ (Table S3). A large  
 171 proportion of the 44 genes containing sites hypomethylated in MQ compared to VQ, were also  
 172 differentially expressed: 6 were over-expressed in MQ (13.6%), 14 genes were lower expressed in  
 173 MQ (31.8%) compared to VQ, while 24 (54.5%) did not differ in expression. These proportions  
 174 of differentially expressed genes are significantly higher than those found in all genes (10.6% and  
 175 15.8%, respectively;  $\chi^2$ : 9.64, df = 2, p-value = 0.008), indicating an important role of DNA  
 176 methylation in the regulation of age-specific expression.



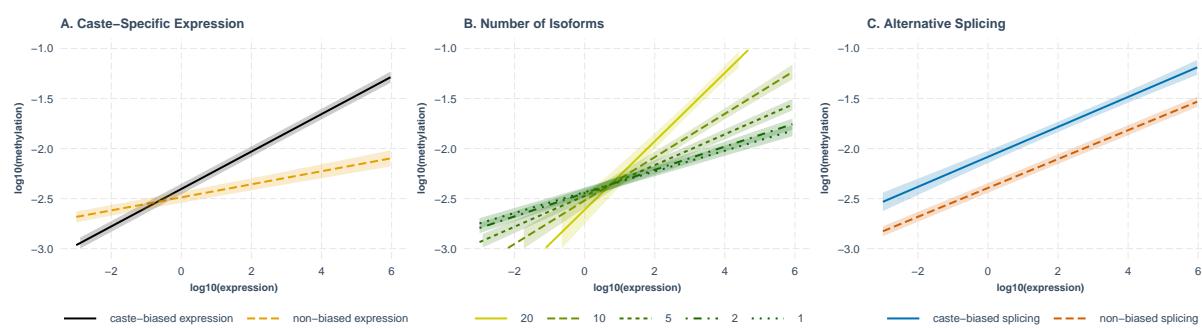
**Figure 5:** Mean methylation level per gene region for groups of differentially expressed genes. HKG = house-keeping genes, defined as non-differentially expressed genes, with expression counts greater than median expression.

177 Furthermore, we found that differentially expressed genes (DEGs: significantly up- or down-  
178 regulated between pairs of phenotypes) had unique, phenotype-independent methylation sig-  
179 natures (Fig. 5). For instance, while the full set of DEGs have a mean methylation level of  
180 7.4% in coding regions, genes with over-expression in MQ or MK compared to VQ, or in MQ  
181 versus FW, have very low coding region methylation (2.3, 3.2% and 4.0%, respectively). Genes  
182 overexpressed in MQ and MK compared to VQ also have high methylation in 3'-flanks (3.5 and  
183 3.1%, respectively), compared to all DEGs (2.2%) (Fig. 5). Surprisingly, within each of these

184 DEG groups, variation among phenotypes was low, with standard deviation among samples  
185 ranging from 0.10 to 0.53. These patterns point towards a complex relationship between DNA  
186 methylation and caste- or age-specific gene expression in *M. natalensis*.

187 *Variation in gene body methylation influenced by expression level, caste-specific expression*  
188 *and alternative splicing*

189 To better understand the variation in methylation levels among genes, we first investigated the  
190 influence of expression level. We found a significant positive correlation between methylation  
191 level of coding sites and expression level, which ranged from 0.208 (p-value =  $2.0 \times 10^{-176}$ ) to  
192 0.254 (p-value =  $6.9 \times 10^{-265}$ ; spearman's rank correlation) per sample. This confirms previous  
193 findings for Hymenoptera (Bonasio *et al.*, 2012; Patalano *et al.*, 2015; Libbrecht *et al.*, 2016)  
194 and a termite (Glastad *et al.*, 2016). Among genes whose expression differed significantly among  
195 phenotypes (DEGs), we found a significant positive interaction with expression, with a linear  
196 regression predicting higher methylation for DEGs compared to nonDEGs for expression levels  
197 greater than the 4th percentile (Fig. 6A). We also found that methylation level increases with  
198 the number of isoforms per gene, when controlling for expression level, with methylation level  
199 predicted to be higher for multiple isoform genes at expression levels greater than the 17th  
200 percentile (Fig. 6B). For genes which are putatively differentially spliced among phenotypes  
201 (significant differential exon expression), a linear regression predicts significantly higher methy-  
202 lation regardless of expression level (Fig. 6C). These results suggest an important role of DNA  
203 methylation in the regulation of gene expression level, especially when regulating caste- and  
204 age-specific transcription and splicing. The regulation of caste-specific splicing via DNA methy-  
205 lation may be universal in eusocial insects since similar evidence has been found in honeybees  
206 (Lyko *et al.*, 2010), ants (Bonasio *et al.*, 2012; Libbrecht *et al.*, 2016), and the lower termite, *Z.*  
207 *nevadensis* (Glastad *et al.*, 2016).



**Figure 6:** Linear models, relating differential gene and isoform expression to methylation level. **A.** Differentially expressed genes are more highly methylated when accounting for expression level. **B.** Methylation increases with increasing number of isoforms, relative to expression level. **C.** Genes that show age- and caste-specific alternative splicing are more highly methylated, regardless of expression. Models have the form:  $\log_{10}(\text{methylation level}) \sim \log_{10}(\text{expression level}) * \text{variable} + (1|\text{sample})$ .

## 208 Conclusions

209 We report a strong correlation of DNA methylation patterns with caste- and age-specific gene  
210 expression and alternative splicing in the fat body of the higher termite, *M. natalensis*. These  
211 results offer further support for the importance of fat body transcription (Séité *et al.*, 2022) and  
212 its regulation for the extreme longevity and fecundity of termite queens. We also confirm the  
213 importance of replication in methylation analyses due to higher variation in methylation between  
214 colonies than between castes, a point of contention among previous studies in Hymenoptera (Lib-  
215 brecht *et al.*, 2016). Furthermore, and importantly, we present evidence for unique methylation  
216 signatures which are stable between phenotypes but differ especially between groups of genes  
217 with age-biased expression. For example, genes with higher expression in mature reproductives  
218 (MQ and MK) than in young reproductives (VQ) have relatively low coding region methylation  
219 but high methylation in 3'-flanks among all phenotypes compared to other DEGs. We believe  
220 this is the first time such a methylation pattern has been presented for social insects and suggests  
221 its generality should be tested on further species. We show for the first time, how DNA methy-  
222 lation may be responsible for regulating genes which are central to termite queens maintaining  
223 high fertility at extreme ages. For the 20-year old, highly fertile queens, we present evidence  
224 for well-maintained DNA methylation, in support of an apparent lack of epigenetic drift, a well  
225 established hallmark of ageing (López-Otín *et al.*, 2013). Several genes with important roles

226 in ageing and fertility, on the other hand, contain sites with significantly reduced methylation  
227 levels in mature queens compared to young, virgin queens, many of which have significantly  
228 different expression levels in old compared to young queens.

229 **Methods**

230 *DNA extractions and sequencing*

231 Total genomic DNA from the 12 termite samples (female workers, young virgin queens, mature  
232 queens and kings; see Table S1 and Séité *et al.* 2022 for sampling) was extracted from fat body  
233 using DNeasy Blood and Tissue kit (Qiagen), including RNase A treatment (Qiagen), accord-  
234 ing to the manufacturer's instructions. Library construction was performed using the Premium  
235 Reduced Representation Bisulfite Sequencing kit (Diagenode). Briefly, for each sample, 100  
236 ng of genomic DNA were digested using MspI for 12 hours at 37°C. DNA ends were repaired  
237 and Diagenode indexed adaptors were ligated to each end of the repaired DNA. Each ligated  
238 DNA was quantified by qPCR using the Kapa Library quantification kit (Kapabiosystems) on  
239 a LightCycler 480 (Roche Life Science) prior to pooling (4, 5 or 6 samples per pool). Each pool  
240 was subjected to bisulfite conversion and desalting. Optimal PCR cycle number was determined  
241 by qPCR (Kapa Library quantification kit, Kapabiosystems) before the final enrichment PCR.  
242 Once purified using magnetic beads (AMPure XP, Beckman Coulter), library pools were veri-  
243 fied on Fragment Analyzer (AATI) and precisely quantified by qPCR using the Kapa Library  
244 quantification kit (Kapabiosystems). Each pool was denatured, diluted and spiked with a 10%  
245 phiX Illumina library before clustering. Clustering and sequencing were performed in single  
246 read 100 nt, 1 lane per pool, according to the manufacturer's instructions on a Hiseq2500 us-  
247 ing Rapid V2 clustering and SBS reagents. Base calling was performed using the Real-Time  
248 Analysis Software and demultiplexing was performed using the bcl2fastq software, both from  
249 Illumina. Non-conversion rate of bisulfite treatment was estimated with a spike-in control, and  
250 only samples with a non-conversion rate lower than 5% were kept for further analysis.

251 *Preparation of RRBS data*

252 The RRBS reads were prepared by following the BISMARK protocol (Krueger and Andrews,  
253 2011). This included adapter trimming with TRIM GALORE, v.0.4.4-dev (<https://github.com/FelixKrueger/TrimGalore>) at default settings with the additional –rrbs argument. Sub-  
254 sequently, BISMARK was used to analyse methylation states. The *M. natalensis* genome (Poulsen  
255 *et al.*, 2014) was indexed using the bismark\_genome\_preparation command, then sequenced reads  
256 were mapped to the genome using bowtie2, version 2.3.4.3 (Langmead and Salzberg, 2012). Oth-  
257 erwise, standard parameters were implemented for the BISMARK pipeline.

259 *Methylation analyses*

260 We extracted methylation and read coverage information from the thus produced bam files  
261 with the BISMARK\_METHYLATION\_EXTRACTOR command, with the arguments –scaffolds and  
262 –bedGraph. We only considered sites to which at least 5 reads mapped. Based on the non-  
263 conversion rate of a spike-in control, a binomial test was carried out to confirm the significance  
264 of a measured proportion of non-converted, and therefore putatively methylated, reads, as pre-  
265 viously performed by Glastad *et al.* (Glastad *et al.*, 2016). P-values were FDR corrected,  
266 and only corrected p-values < 0.05 were deemed methylated, and were otherwise counted as  
267 non-methylated. Sequenced cytosines ( $\geq 5$  reads) were annotated with gene features - exons,  
268 introns, 10kb flanking regions, repetitive regions - based on information stored in two GFF files,  
269 containing protein coding and repeat element annotations (Harrison *et al.*, 2018; Poulsen *et al.*,  
270 2014).

271 *Principal component analysis (PCA)*

272 The PCA analysis was performed in R, version 4.0.2 (R Core Team, 2016). For each CpG site  
273 that was covered by at least 5 reads in all 12 samples, we measured variance in methylation  
274 among samples and selected the 1000 most variable sites. The PCA was computed on these  
275 top variable sites with the PRCOMP function and the first two PCs were plotted with ggplot2  
276 (Wickham *et al.*, 2016).

277 *Regression models*

278 For each gene, average methylation level was calculated per feature type (exons, introns, 5'-  
279 flank and 3'-flank) and per sample. All regression analyses were performed on this data set.  
280 The following variables were considered:

Methylation:	average proportion of methylated reads in %	continuous 0-100
Expression:	normalised expression level, taken from (Séité <i>et al.</i> , 2022)	continuous $\geq 0$
Feature:	genic region	categorical (exon, intron, 5'-flank, 3'-flank)
Caste:		categorical (FW, VQ, MQ, MK)
281 Transcripts:	number of transcripts per locus	continuous, positive integers
Colony:		categorical (3, 5, 6, 7)
DE:	division of genes into DEG and nonDEG (Séité <i>et al.</i> , 2022)	categorical (DE, nonDE)
DMG:	whether gene contains differentially methylated CpGs	categorical (DMG, nonDMG)
AS:	whether gene has differential exon expression between castes	categorical (AS, nonAS)

282 ANOVAs and ANCOVAs were also performed in R with the ANOVA\_TEST function from the  
283 rstatix library (Kassambara, 2021). For graphical representations, we used the LMER function  
284 from the lme4 package (Bates *et al.*, 2015) to create the model and INTERACT\_PLOT from the  
285 interactions package (Long, 2019) for plotting. In each case, we log-transformed expression and  
286 modelled non-liner regression of methylation with the POLY function, using as many polynomials  
287 as were significant. The following variables were included as co-factors: number of transcripts per  
288 gene, caste membership, genomic feature (exon, intron, 5'-flank, 3'-flank), differential expression;  
289 with colony membership as the random effects term. For example, to relate methylation to  
290 expression by caste and differential expression, while controlling for colony membership:

*#model:*

```
lmer(log(expression+0.01) ~ poly(Methylation, 2) * Caste * de + (1|Colony),  
data = na.omit(meth[meth$Feature == "cds",]))  
  
#plot:  
interact_plot(expr.lmer, pred = Methylation, modx = Caste, \  
modx2 = de, interval = T)
```

291 *Detecting differential methylation*

292 To detect significant differences in methylation between phenotypes, we used the R package  
293 methylKit, version 1.11.1 (Akalin *et al.*, 2012). We analysed differential methylation between all  
294 pairs of the four phenotypes (FW, VQ, MQ, MK) and for each of these comparisons only included  
295 CpGs, for which at least 10 reads existed for all 6 samples (3 replicates x 2 phenotypes). A  
296 difference in methylation was only considered significant if it were at least 25 percentage points  
297 and with an adjusted p-value < 0.05. Each CpG, which was significant within any of these  
298 comparisons, was considered a differentially methylated site (DMS). To validate the numbers of  
299 DMS between pairs of castes, we repeated this analysis for 1000 random pairings of 3 samples,  
300 sampled without replacement, and recorded the frequency of DMS in each case.

301 *GO term enrichment of robustly methylated genes*

302 We extracted the unique list of genes which contained CpGs methylated in all 12 samples (Fig.  
303 2A). A GO-term enrichment test was performed on this list of genes with topGO (version  
304 2.34.075) (Alexa *et al.*, 2010), using the classic algorithm. Node size was set to 5, Fisher exact  
305 tests were applied, and we only kept GO terms that matched with 2 genes at least and with a  
306 and FDR-value < 0.2.

307 *Alternative splicing*

308 Alternative splicing was estimated for each gene by measuring differential exon expression with  
309 the package DEXseq (Li *et al.*, 2015). This pipeline involves first formatting the gff and then  
310 extracting exon read counts from sam files. These sam files had been created in a previous study

311 by mapping RNAseq reads to the *M. natalensis* genome (Séité *et al.*, 2022). The DEXseq pipeline  
312 was followed at default settings and for each of the four castes compared to the other three castes,  
313 we determined genes containing significantly differentially expressed exons (adjusted p-value  
314 < 0.05) relative to whole gene expression. These genes were considered putatively alternatively  
315 spliced.

316 Additionally, we assembled a genome-guided transcriptome from RNAseq data (accessions:  
317 SAMN17088123-SAMN17088147) (Séité *et al.*, 2022), using the new tuxedo protocol (Pertea  
318 *et al.*, 2016). Raw reads were trimmed using Trimmomatic (v0.38) (Bolger *et al.*, 2014) with  
319 parameters TRAILING:25 LEADING:25 SLIDINGWINDOW:4:20 AVGQUAL:20 MINLEN:50.  
320 Only reads with both pairs after trimming were used for the further analysis. The trimmed  
321 RNAseq reads were mapped to the genome with Hisat2 (v2.1.0) (Kim *et al.*, 2019) at default  
322 settings for each library. Individual transcriptomes were assembled and merged into one with  
323 StringTie (v1.3.4) (Pertea *et al.*, 2016). Numbers of transcripts per annotated gene were then  
324 extracted from the resulting gff.

325 *Differential expression*

326 All data on gene expression levels and caste- and age-biased expression were obtained from Séité  
327 *et al.* (2022).

328 **Availability of data and material**

329 RRBS sequences have been deposited on NCBI, available under the accession PR-  
330 JNA742659. Scripts and detailed methods are available on the github repository  
331 [https://github.com/MCH74/Mnat\\_Methylation](https://github.com/MCH74/Mnat_Methylation).

332 **Competing interests**

333 The authors declare that they have no competing interests.

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337 **Authors' contributions**

338 M.V.-C. conceived the project and provided biological materials. D.S.D and M.V.-C. collected  
339 wild samples. S.G. carried out RRBS services. M.C.H. & E.D. carried out all bioinformat-  
340 ics analyses. M.C.H., S.S. & M.V.-C. interpreted data. M.C.H. wrote the manuscript with  
341 contributions from all authors.

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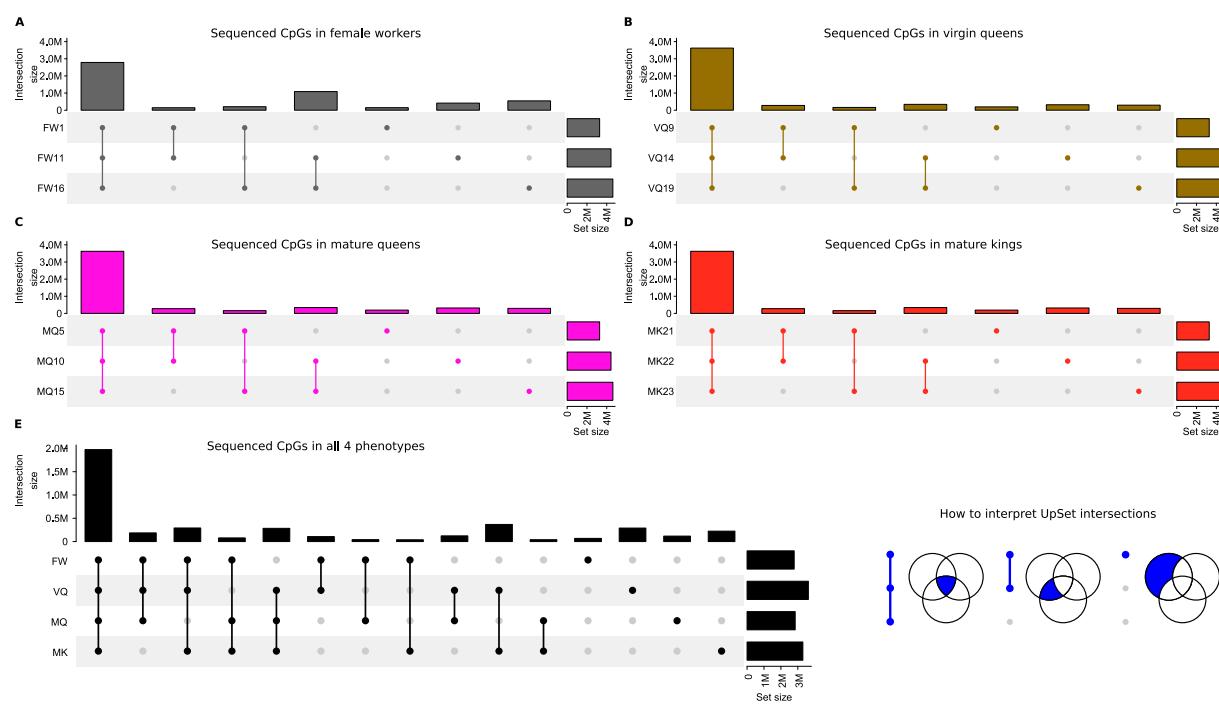
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445 **Supplementary Material**

446 *Supplementary Figures*



**Figure S1: RRBS coverage across 4 phenotypes and 3 replicates.** The UpSet plots in visualise sizes of intersections between sets. The central matrix in each shows with joined, coloured dots, which sets are included in the intersections (see inset at bottom right), the vertical columns show the size of these intersections and the horizontal bars show the set sizes. Specifically, **A.-D.** show numbers of sequenced CpGs for each of the three replicates (horizontal bars) and their overlaps between replicates (vertical bars) in female workers (FW), virgin queens (VQ), mature queens (MQ) and mature kings (MK), respectively. **E.** shows total numbers of sequenced CpGs covered by all four phenotypes (FW, VQ, MQ, MK), and how they overlap between phenotypes. In **E.**, sets are comprised of those CpGs which were sequenced in all three replicates represented by left-most vertical bar in plots **A.-D..**

<sup>447</sup> *Supplementary Tables*

**Table S1:** Summary of the sampling design and sequencing results.

This table contains the origin of the fat body obtained from the 4 *Macrotermes natalensis* phenotypes (female worker, FW; virgin queens, VQ; mature queens, MQ; mature kings, MK) analysed in this study. These termites were collected from field colonies (colony ID) in 2016 in Southern Africa as described in (Séité *et al.*, 2022). The number of individuals pooled per sample, the bisulfite non-conversion rates, total numbers of sequenced reads, and mapping rates are indicated.

The same fat body samples were used to prepare total RNA for transcriptomes (Séité *et al.*, 2022) and for genomic DNA for methylome analyses presented in this manuscript.

Sample-ID	Phenotype	Colony-ID	Nr. pooled individuals	non-conversion rate	Nr. reads	mapping rate
1	FW	3	85	0.9	32.1M	67.3%
11	FW	6	85	0.7	47.4M	68.3%
16	FW	7	85	0.8	57.4M	68.4%
9	VQ	5	10	0.9	47.7M	69.9%
14	VQ	6	10	1.1	59.4M	70.1%
19	VQ	7	10	1.4	48.9M	71.2%
5	MQ	3	1	0.6	35.2M	70.5%
10	MQ	5	1	0.6	61.4M	70.8%
15	MQ	6	1	0.9	45.5M	70.3%
21	MK	5	1	1.1	47.3M	69.8%
22	MK	6	1	0.7	51.7M	70.5%
23	MK	7	1	0.9	40.1M	69.3%

**Table S2:** GO-terms significantly enriched among genes containing robustly methylated CpGs, i.e. in all 12 samples. Shown are all terms with an FDR < 0.2.

	GO.ID	Description	p-value	FDR
1	GO:0030154	cell differentiation	5.2E-04	0.033
2	GO:0048869	cellular developmental process	5.2E-04	0.033
3	GO:0006265	DNA topological change	3.0E-03	0.128
4	GO:0007155	cell adhesion	5.6E-03	0.143
5	GO:0022610	biological adhesion	5.6E-03	0.143
6	GO:0050794	regulation of cellular process	0.011	0.166
7	GO:0050789	regulation of biological process	0.013	0.166
8	GO:0007156	homophilic cell adhesion via plasma membrane adhesion molecules	0.013	0.166
9	GO:0098609	cell-cell adhesion	0.013	0.166
10	GO:0098742	cell-cell adhesion via plasma-membrane adhesion molecules	0.013	0.166
11	GO:0065007	biological regulation	0.016	0.183
12	GO:0007264	small GTPase mediated signal transduction	0.017	0.183

**Table S3:** Genes containing significantly differentially methylated sites between young, virgin queens and mature queens. Dmel & Hsap: ortholog in *Drosophila melanogaster* and *Homo sapiens*. DE: differential expression between VQ & MQ (Séité *et al.*, 2022).

Gene	feature	Dmel	Hsap	PFAM	putative function	DE VQ vs MQ
<b>VQ &lt; MQ</b>						
Mnat_03252	5'-flank	NA	NA	NA	unknown	nonDE
Mnat_04370	5'-flank	Ddc	DDC	Pyridoxal_deC	Copa decarboxylase, lifespan <sup>fb</sup>	VQ
Mnat_09467	CDS1	CG32447	NA	7tm_3	class C G-protein-coupled receptor <sup>pf</sup>	MQ
Mnat_11641	CDS2	Peritrophin-A	NA	CBM_14	chitin-binding, reproduction <sup>fb</sup>	VQ
Mnat_15310	intron1	NA	NA	NA	unknown	nonDE
Mnat_10547	intron3	NA	UGT2B7	UDPGT	UDP-glucuronosyltransferase <sup>up</sup>	VQ
Mnat_16506	intron6	NA	SLC9B2	Na <sub>+</sub> -Exchanger	Na <sub>+</sub> /H <sub>+</sub> antiporter <sup>up</sup>	nonDE
Mnat_10733	intron6	NA	NA	EAT	unknown	nonDE
Mnat_05311	3'-flank	NA	NA	NA	unknown	nonDE
<b>VQ &gt; MQ</b>						
Mnat_00142	5'-flank	side-VI	NA	Ig_3	unknown	nonDE
Mnat_00644	5'-flank	stj	CACNA2D3	VWA_N, VWA_2, VGCC_alpha2	voltage-gated calcium channel <sup>fb</sup>	VQ
Mnat_00686	5'-flank	noc	ZNF503	NA	negative regulation of notch signalling <sup>fb</sup>	nonDE
Mnat_01940	5'-flank	NA	NA	DDE_Tnp_1_7	transposon <sup>up</sup>	nonDE
Mnat_08254	5'-flank	CG15533	NA	Metallophos	sphingomyelinase activity <sup>fb</sup>	MQ
Mnat_10196	5'-flank	fl(2)d	WTAP	Wtap	WMM complex, mRNA methylation and splicing <sup>fb</sup>	nonDE
Mnat_10965	5'-flank	NA	NA	NA	nonDE	
Mnat_11142	5'-flank	Fkbp14	FKBP14	FKBP_C, EF-hand_7	immunophilin, interacts with Notch pathway <sup>fb</sup>	MQ
Mnat_12594	5'-flank	NA	NA	NA	unknown	nonDE
Mnat_15090	5'-flank	CG12581	NA	NA	unknown	VQ
Mnat_17923	5'-flank	scramb1	PLSCR1	Scramblase	scramblase: neurotransmission, apoptosis <sup>fb</sup>	VQ
Mnat_00686	CDS2	noc	ZNF503	NA	negative regulation of notch signalling <sup>fb</sup>	nonDE
Mnat_11151	CDS3	NA	APCDD1	APCDDC	Negative regulator of Wnt signalling <sup>up</sup>	nonDE
Mnat_16530	CDS4	Sytbeta	NA	C2	Synaptotagmin, several cellular functions <sup>fb</sup>	VQ
Mnat_03908	CDS6	NA	NA	NA	unknown	VQ
Mnat_03066	CDS10	CG31075	NA	Aldedh	Aldehyde dehydrogenase <sup>fb</sup>	VQ
Mnat_00817	intron1	NA	NA	C2-set_2	unknown	nonDE
Mnat_02242	intron1	daw	MSTN	TGFb-propeptide, TGF_beta	tricarboxylic acid cycle in fat body and insulin regulation <sup>fb</sup>	MQ
Mnat_03015	intron1	Elk	KCNH8	PAS_9_Ion_trans	voltage-gated potassium channel activity <sup>fb</sup>	MQ
Mnat_05460	intron1	NA	NA	CTNNB1_binding	Wnt signalling <sup>pf</sup>	nonDE
Mnat_08353	intron1	NA	NA	ANF_receptor	receptor <sup>pf</sup>	VQ
Mnat_08440	intron1	NA	NA	NA	unknown	nonDE
Mnat_09896	intron1	CG5160	NA	Ras	GTPase activity <sup>fb</sup>	nonDE
Mnat_12275	intron2	tai	NCOA2	HLH, PAS_11	ecdysone receptor co-activator <sup>fb</sup>	VQ
Mnat_03394	intron3	Sirt6	SIRT6	SIR2	Sirtuin6 <sup>fb</sup> , lifespan	nonDE
Mnat_09845	intron3	NA	NA	7tm_1	G protein-coupled receptor <sup>pf</sup>	nonDE
Mnat_14320	intron5	Skeletor	NA	DM13, DOMON	cell cycle regulation <sup>fb</sup>	VQ
Mnat_00511	intron8	NA	NA	Vitellogenin_N, DUF1943, VWD	Vitellogenin <sup>pf</sup> , fertility	MQ
Mnat_04048	intron10	Rab11	RAB11A	Ras, Lactamase_B, Lactamase_B-2	Ras-like GTPase <sup>fb</sup>	MQ
Mnat_05339	intron12	NA	NA	NA	unknown	nonDE
Mnat_01396	intron14	shg	NA	Cadherin, Laminin_G_2, Cadherin_C	cadherin <sup>fb</sup>	VQ
Mnat_12633	intron18	Pde11	PDE5A	GAF, PDEase_I	Phosphodiesterase 11, signalling <sup>fb</sup>	VQ
Mnat_11129	intron140	bt	TTN	I-set, Pkinase	Projectin, muscle protein <sup>fb</sup>	VQ
Mnat_01803	3'-flank	CG8405	TMEM259	Membralin	regulation of misfolded proteins <sup>up</sup>	nonDE
Mnat_02376	3'-flank	NA	NA	LRR_8	unknown	nonDE
Mnat_02952	3'-flank	NA	NA	NA	unknown	nonDE
Mnat_05525	3'-flank	CIC_c	CLCN3	Voltage_CLC, CBS	chloride channel <sup>fb</sup>	VQ
Mnat_06053	3'-flank	1(2)37Cc	PHB	Band_7	larval metabolism <sup>fb</sup>	nonDE
Mnat_07417	3'-flank	NA	NA	NA	unknown	nonDE
Mnat_10837	3'-flank	NA	NA	zf-met, zf-C2H2_6, P zf-C2H2	DNA/RNA-binding, transcriptional regulation <sup>pf</sup>	nonDE
Mnat_13326	3'-flank	chico	NA	NA	substrate of InR in IIS pathway <sup>fb</sup>	VQ
Mnat_13488	3'-flank	NA	NA	DDE_3	endonuclease <sup>fb</sup>	nonDE
Mnat_14386	3'-flank	NA	NA	DUF4817, DDE_3	DNA-binding and endonuclease <sup>pf</sup>	nonDE
Mnat_14747	3'-flank	NA	NA	NA	unknown	nonDE
Mnat_16347	3'-flank	NA	NA	7tm_6	odorant receptor <sup>pf</sup>	nonDE

