

1 **Opportunities and limitations of reduced representation bisulfite sequencing in plant**
2 **ecological epigenomics**

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14
15 **Summary:** Investigating the features and implications of epigenetic mechanisms across the
16 breadth of organisms and ecosystems is important for understanding the ecological relevance
17 of epigenetics. Several cost-effective reduced representation bisulfite sequencing approaches
18 (RRBS) have been recently developed and applied to different organisms that lack a well-
19 annotated reference genome. These new approaches improve the assessment of epigenetic
20 diversity in ecological settings and may provide functional insights. We assess here the
21 opportunities and limitations of RRBS in non-model plant species. Well-thought out
22 experimental designs that include complementary gene expression studies, and the
23 improvement of genomics resources for the target group promise to maximize impact of
24 future RRBS studies.

25
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28
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34 **I. Introduction**

35 Ecological epigenetics aims to understand the unique contributions of epigenetic
36 mechanisms to ecological and evolutionary processes (Bossdorf *et al.*, 2008; Richards *et al.*,
37 2017). Several studies have shown that DNA methylation variation correlates with ecological
38 factors, suggesting a potential role for epigenetics in adaptation (Verhoeven *et al.*, 2016;
39 Richards *et al.*, 2017). However, the low genomic resolution of many studies on non-model
40 organisms precludes pinpointing causality of epigenetic effects, and the peculiarities of the
41 few plant and animal model organisms may impede generalizations (e.g., Lyko, 2001; Alonso
42 *et al.*, 2015). Recently, we discussed how high resolution epigenomics tools must be
43 combined with ecologically-relevant experimental settings to explore the importance of
44 epigenetic mechanisms (Richards *et al.*, 2017). We also argued that in order to evaluate the
45 relevance of epigenetic mechanisms to ecology and evolution, these approaches need to be
46 applied across a diversity of organisms and conditions. However, powerful epigenomic
47 methodologies have largely been accessible for only a few model species. The ‘gold
48 standard’ of bisulfite sequencing applied to whole genomes (WGBS) evaluates methylation
49 status for essentially every cytosine in a genome (Frommer *et al.*, 1992; Harris *et al.*, 2010; Li
50 & Tollefsbol, 2011; Olova *et al.*, 2018), but this approach is still limited in application to
51 species with a high-quality reference genome (e.g. Niederhuth *et al.*, 2016). Furthermore, this
52 approach is prohibitively expensive for large experimental designs, particularly for average to
53 large plant genomes.

54 Several recently developed approaches based on reduced-representation bisulfite
55 sequencing methods (RRBS) provide cost-effective alternatives to WGBS, by interrogating
56 only a representative fraction of the genome (Gu *et al.*, 2011; Wang *et al.*, 2015; Trucchi *et al.*
57 *et al.*, 2016; van Gurp *et al.*, 2016). RRBS approaches are scalable for ecological experimental
58 designs, can be used on organisms without reference genomes, and allow for greater
59 resolution than previous marker-based approaches. RRBS reads can also be mapped to a
60 reference or draft reference genome when available (Gugger *et al.*, 2016; Lea *et al.*, 2016;
61 Trucchi *et al.*, 2016; Weyrich *et al.*, 2016), and may provide functional insights. For the
62 species that lack a reference genome, RRBS studies can generate accession-specific
63 references for only the loci that are interrogated, either by including non-bisulfite-converted
64 samples in the sequencing (e.g. for bsRADseq, Trucchi *et al.*, 2016) or by inferring the un-
65 converted reference from the bisulfite treated reads themselves (e.g. epiGBS, van Gurp *et al.*,
66 2016). These attributes combined with cost-efficiency make RRBS methods attractive
67 options for studies that address ecological and evolutionary epigenetics in essentially any

68 organism. However, it is important to evaluate their strengths along with any limitations to
69 identify which research questions can be fruitfully addressed.

70

71 **II. RRBS loci as genome-wide epigenetic markers**

72 RRBS methods are more powerful than previous methods (such as methylation-
73 sensitive amplified fragment length polymorphism or MS-AFLP/MSAP; see e.g., Schrey *et*
74 *al.*, 2013) for exploring patterns of DNA methylation variation at a genome-wide scale. The
75 increase in power is due to the fact that RRBS typically reviews multiple cytosine positions
76 within each of tens of thousands of fragments. Unlike earlier methods, RRBS data is
77 quantitative at nucleotide resolution, which reflects the biology of DNA methylation across
78 cells in a tissue sample. RRBS methods provide methylation information at different
79 sequence contexts (CG, CHG, CHH). Methylation in these different DNA contexts is
80 correlated to distinct functions, regulated by different molecular pathways, and known to
81 have different levels of heritability and environmental-sensitivity, thus providing further tools
82 for dissecting natural patterns of DNA methylation (Dubin *et al.*, 2015; Niederhuth *et al.*,
83 2016; Trucchi *et al.*, 2016; Niederhuth & Schmitz, 2017). RRBS data can be integrated to
84 quantify overall similarity among individuals in DNA methylation, which supplies a basis for
85 describing patterns of epigenetic variation within and among natural populations.

86 Such descriptive population epigenetic measures provide useful insights about the
87 distribution of epigenetic variation. For instance, to what extent is natural epigenetic
88 population structure correlated to underlying genetic population structure, and to what extent
89 is it correlated with environmental variation? High correlation between epigenetic and
90 genetic structure has been observed in several studies of natural populations of *Arabidopsis*
91 *thaliana* (Dubin *et al.*, 2015; Kawakatsu *et al.*, 2016), experimental populations of maize
92 (Eichten *et al.*, 2013), and recombinant inbred lines (RILs) of soybean (Schmitz *et al.*, 2013),
93 suggesting that a significant portion of epigenetic variation is under genetic control. These
94 studies rely on detecting associations between differentially methylated regions (DMR) and
95 neighboring genetic polymorphisms to indicate genetic control in *cis* over DNA methylation.
96 Associations in *trans* have also been detected, for example between CHH methylation and
97 genetic variation in the chromomethyltransferase CMT2 (Dubin *et al.*, 2015). However, *cis*
98 and *trans* correlations can also arise in the absence of genetic control, when a spontaneous
99 epimutation becomes stably inherited (Taudt *et al.*, 2016). In addition, some studies have
100 reported that a component of epigenetic population structure was not explained by genetic
101 structure, and was instead associated with ecological conditions (e.g. Richards *et al.*, 2012;

102 Dubin *et al.*, 2015; Foust *et al.*, 2016; Kawakatsu *et al.*, 2016). This suggests that epigenetics
103 can contribute directly or indirectly to adaptation: either *i*) because epigenetic changes are
104 induced by environmental conditions, and provide a capacity for phenotypic plasticity or
105 longer-term heritable responses, and/or *ii*) because the epigenetic variation that does not
106 correlate to overall (neutral) genetic population structure can be under control by individual
107 genetic loci.

108 In addition to characterizing natural DNA methylation variation, the high heritability
109 of cytosine methylation in plants suggests that RRBS-loci could be used as markers for
110 linkage mapping purposes in crosses where genetic variation is limited or absent (Johannes *et al.*
111 *et al.*, 2009; Cortijo *et al.*, 2014; Dapp *et al.*, 2015; Hofmeister *et al.*, 2017). Also, general
112 characteristics of DNA methylation dynamics, such as transgenerational stability,
113 epimutation and reversal rates, and response to experimental or field conditions of interest,
114 can be investigated by looking at many, but not necessarily all, loci in the genome, and may
115 thus be addressed with RRBS approaches.

116

117 **III. Exploiting functional annotation of RRBS loci**

118 The DNA sequence contained in RRBS fragments holds promise for providing
119 information about the function of the genomic regions that show DNA methylation
120 differences (Fig. 1). In particular, epigenetic changes at enhancer elements can drive gene
121 expression alterations and have functional consequences (Taudt *et al.*, 2016). RRBS methods
122 were initially developed for studies in mammals where a large fraction of gene promoters are
123 associated with GC-rich areas (CpG islands) and methylation status of these areas has
124 functional consequences for gene regulation (Meissner *et al.*, 2005). Using restriction
125 enzymes that bias toward GC-rich sites (such as MspI), RRBS in mammals evaluates
126 methylation in 80-90% of CpG islands by targeting only a small portion of the total genome
127 (Smith *et al.*, 2009). Typical plant genomes lack CpG islands and MspI-based reduced
128 representation of genomes does not result in a bias towards gene promoters (Hsu *et al.*, 2017).
129 However, bias to either gene bodies or gene promoters can be achieved in plants by selecting
130 different restriction enzymes, and increasing overall genome representation. For instance,
131 RRBS in maize using the frequent cutter MseI provides a representation of >80% of the
132 annotated gene promoters when coverage is increased to ~19% of the total genome. With a
133 different enzyme (CviQI), >80% of gene bodies were included by sequencing ~15% of the
134 genome (Hsu *et al.*, 2017). The enrichment for functional components of the genome may not
135 be as extreme as in mammals, but it does allow for functional insights. For instance, Hsu *et*

136 *al.* (2017) identified genes with tissue-specific expression associated with specific promoter
137 DNA methylation profiles. In addition, complementary expression analyses with RNAseq or
138 qPCR will complement RRBS datasets, potentially uncovering gene expression alterations
139 associated with DNA methylation variation.

140

141 **IV. Limitations of RRBS methods for non-model species**

142 Although RRBS can target functional regions of a genome, identification of the
143 genomic context of RRBS loci in non-model species is typically restricted to fragments that
144 have homology to annotated species (Fig. 1). This approach has known limitations since
145 genes and their function evolve over time, which may prevent proper interpretation of the
146 information obtained in non-model species (Pavey *et al.*, 2012; Alvarez *et al.*, 2015). In the
147 absence of a reference genome, a reference transcriptome could help improve functional
148 predictions. In practice however, even if a large portion of the RRBS fragments overlap with
149 a well annotated transcriptome (e.g., ca 10,000 of 36,000 RRBS fragments in *Spartina*,
150 Alvarez *et al.*, in review; >40% of bsRADseq in *Heliosperma*; Trucchi *et al.*, 2016) or can be
151 annotated with known plant genes (10-15% of epiGBS loci in six grassland species, Van
152 Moorsel *et al.*, 2018), only some of the fragments actually overlap the 5' end of genes
153 (Alvarez *et al.*, in review) where increased DNA methylation has been correlated with gene
154 silencing (Niederhuth *et al.*, 2016; Niederhuth & Schmitz, 2017). The functional relevance of
155 gene body methylation outside of the 5' end in plants appears to vary by context and across
156 taxa (Niederhuth & Schmitz, 2017), and often gene body methylation is not correlated or only
157 weakly correlated to gene expression (Bewick & Schmitz, 2017). While methylation of the
158 promoter region is highly correlated with silencing, without a well-annotated reference
159 genome of the target species or a close relative, it is difficult or even impossible to identify
160 those RRBS fragments that overlap promoter regions. Further, obtaining sufficient coverage
161 of the genome may be prohibitive for plants with average to large genomes.

162 RRBS approaches allow for more power than earlier methods to detect outlier loci or
163 identify loci with high F_{ST} (e.g., Platt *et al.*, 2015), which suggests selection on ecologically
164 important genomic regions (see also McKinney *et al.*, 2017 for a discussion of such an
165 approach). Unlike DNA sequence information that is generally organised in large (e.g.
166 several megabases) linkage blocks shaped by recombination, co-inheritance of epigenetic
167 signals may be less stable and only locally restricted to one or a few neighboring genomic
168 elements that may be missed in reduced representation methods. Similarly, for traits that are

169 controlled by relatively few functional loci, these may simply be missed in RRBS. This
170 problem is amplified in species with large and complex genomes.

171 A further difficulty for all RRBS approaches is the identification of differentially
172 methylated regions (DMRs). Studies in a variety of species have found that methylation
173 changes across large chromosomal stretches (DMRs) are more likely to influence
174 transcriptional activity at nearby loci, and contribute to phenotypic change than at single
175 cytosines (DMPs) (reviewed in Richards *et al.*, 2017). However, DMRs are still difficult to
176 define even in whole genome studies. The short fragments interrogated with RRBS methods
177 (typically less than 500 bp) will contain only a few cytosine positions, and calling DMRs
178 with statistical confidence with such data will be difficult in most cases (Fig. 1). Hence, most
179 RRBS studies will be limited to calling DMPs, with their inherent stochasticity.

180 The evolutionary history of all plant genomes has been shaped by polyploidization
181 and hybridization, which have played a major role in plant diversification and adaptation
182 (e.g., Van de Peer *et al.*, 2017). Sequencing approaches generally will require more
183 sequencing depth to identify all copies of duplicated loci, particularly for those with high
184 levels of heterozygosity, and this problem may be exacerbated with short fragments that have
185 less discriminatory power. This means that the number of polymorphisms that define
186 different copies at a given locus will grade into the number of polymorphisms that define
187 different locations within the genome. This level of information about the genomic landscape
188 is limited to very few non-model species, but could have profound impacts on understanding
189 the importance of both sequence level and methylation variation for ecology and evolution.

190 Finally, unravelling the extent to which epigenetic variants are genetically controlled
191 by or at least partly autonomous from genetic variants in different systems and environmental
192 settings remains a key challenge for understanding the ecological and evolutionary role of
193 epigenetic variation (Richards *et al.*, 2017). In principle, this issue is better addressed with
194 whole-genome data than with a reduced representation data. Reduced representation data
195 provide adequate information to estimate overall genetic and epigenetic population structure,
196 and thus to evaluate the overall correlation between the two. But in absence of full genome
197 data RRBS is limited in helping pin point the genetic determinants of individual epigenetic
198 variants.

199

200 **V. Maximising the impact of RRBS in plants**

201 RRBS approaches allow for great power to detect patterns of variation in the
202 epigenomic landscape, either as heritable signals or as plastic responses to environmental

203 conditions or experimental treatments. However, confirming local adaptation requires
204 detecting specific patterns of organismal response in reciprocal transplant studies in the field
205 or in experiments in controlled environments, ideally by controlling for any genetic influence
206 (Richards *et al.*, 2010). A careful design of experimental conditions is particularly important
207 for assessing epigenetic variation, which has fractions that are environmentally or
208 developmentally labile (Richards *et al.*, 2010, 2017). Measuring epigenetic mechanisms with
209 a proper experimental design can provide information about changes that underlie phenotypic
210 plasticity, and identify changes that are correlated to genetic differences or habitat of origin.
211 Analyzing progeny across at least three generations will also better assess transgenerational
212 heritability of the markers surveyed, but careful consideration of the environment in which to
213 grow these offspring is required.

214 The flexibility of the RRBS protocols allows for several technical ways to improve
215 impact. For instance, the choice of restriction enzymes determines what portions of the
216 genome are sampled. Methylation-sensitive enzymes will target areas in plant genomes that
217 are biased away from heavily methylated repetitive regions, and thus enrich towards coding
218 regions. But using these enzymes will increase the probability of missing data, particularly
219 within DMRs since individuals that are methylated at the recognition site will not be
220 represented. An enzyme with a GC-rich restriction site will also bias against repetitive
221 regions since several transposable elements (TEs) are associated with regions of the genome
222 that are more AT-rich (Le *et al.*, 2000). Furthermore, more frequent cutters (with shorter
223 recognition sequences) will increase representation of the genome regardless of genomic
224 context. Improvements can also come from using platforms that produce longer reads (e.g.
225 MiSeq instead of HiSeq) or by optimizing libraries to get information across larger regions
226 with paired-end sequencing approaches (e.g., up to 800 bp for bsRADseq using Illumina).
227 This increases the likelihood of annotation and calling of DMRs, and potentially identifying
228 promoters.

229 DNA methylation analyses require some additional considerations since it can be
230 difficult to distinguish among substitutions and epiallele changes in bisulfite sequencing. In
231 particular, mutations of either C or G to an A or T can appear to be an epimutation since
232 bisulfite treatment deaminates un-methylated cytosines to uracil, which then pairs with
233 thymine through PCR amplification. A single reference genome does not provide the
234 information needed to discriminate these possibilities. Because of the cost advantage of
235 RRBS compared to WGBS, unconverted references for each accession can be sequenced

236 even for large experimental designs for differentiating genetic variation from methylation
237 variation among individuals.

238

239 **VI. Conclusions**

240 In the past few years, several RRBS methodologies have emerged, increasing the potential
241 and broadening the scope for epigenetics studies in non-model species. While these
242 methodologies improve resolution for marker-based approaches, they have limitations for
243 functional conclusions in species that lack a good reference genome (Fig. 1). These
244 limitations result from the difficulty of targeting the RRBS fragments towards the most
245 functionally relevant contexts for DNA methylation: the promoter regions and the 5' end of
246 transcribed regions. Although approaches exist to enrich for these specific portions of the
247 genome, generating a draft reference genome will be imperative to locate the promoter
248 regions, and allow for better exploitation of RRBS data. Improving genomics resources in a
249 variety of organisms is an essential next step for understanding the importance of epigenetic
250 mechanisms in ecology and evolution.

251

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261

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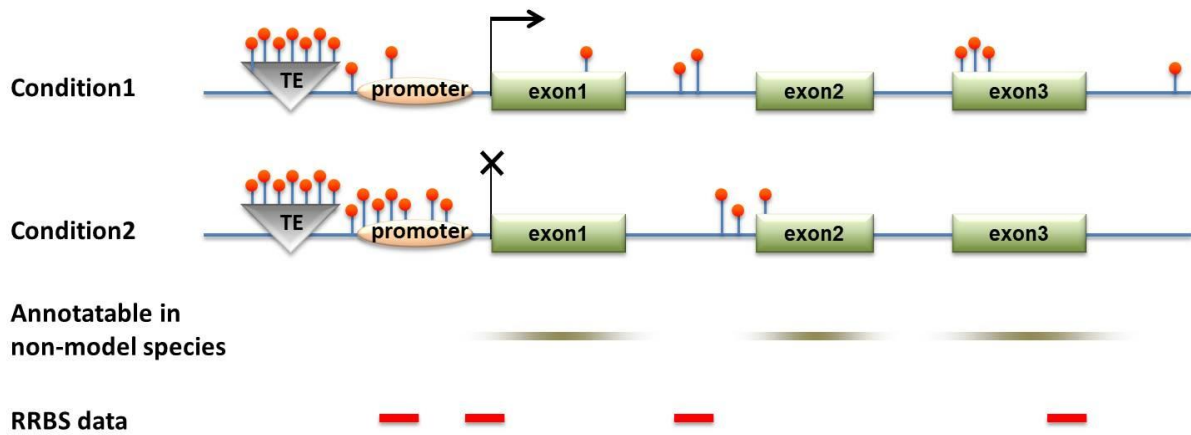
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380 **Figure legend.**

381 **Figure 1.** Typically, studies in ecological epigenetics will be interested in methylation
382 differences that are associated with two different environmental conditions as shown in this
383 cartoon. RRBS data can provide functional insight in non-model species (e.g. the left most
384 RRBS locus), but detecting the genomic context of RRBS fragments is difficult in the
385 absence of a reference genome. In addition, the number of cytosines contained per RRBS
386 locus may be insufficient to call DMRs, hence RRBS analyses will be limited to
387 calling DMPs.

388



389