Methylomes reveal recent evolutionary changes in populations of two plant species

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Abstract

Plant DNA methylation changes occur hundreds up to thousands times faster than DNA mutations and can be transmitted transgenerationally, making them useful for studying population-scale patterns in clonal or selfing species. However, a state-of-the-art approach to use them for inferring population genetic processes and demographic histories is lacking. To address this, we compare evolutionary signatures extracted from CG methylomes and genomes in *Arabidopsis thaliana* and *Brachypodium distachyon*. While methylation variants (SMPs) are less effective than genetic variants (SNPs) for identifying population differentiation in *A. thaliana*, they can classify phenotypically divergent *B. distachyon* subgroups that are otherwise genetically identical. The site frequency spectra generated using methylation sites from varied genomic locations and evolutionary conservation exhibit similar shapes indicating minimal noise when jointly analyzing all CG sites. Nucleotide diversity is three orders of magnitude higher for methylation variants compared to genetic variants in both species, driven by the higher epimutation rate. Correlations between SNPs and SMPs in nucleotide diversity and allele frequencies at gene exons are weak or absent in *A. thaliana*, possibly because the two sources of variation reflect evolutionary forces acting at different timescales. Linkage disequilibrium quickly decays within 250bp for methylation variants in both plant species suggesting their versatility for evolutionary analyses. Finally, we developed a deep learning-based demographic inference approach and identified recent population expansions in *A. thaliana* and *B. distachyon* using methylation variants that were not identified when using genetic variants. Our study demonstrates the unique evolutionary insights provided by methylomes that genetic variation alone cannot reveal.

Keywords: Methylation site frequency spectra, demographic inference, deep learning, Tajima's *D*, linkage disequilibrium, nucleotide diversity, clocklike regions, gene body methylation, *Arabidopsis thaliana*, *Brachypodium distachyon*

Background

Understanding how variation is partitioned within and between populations is a central goal in evolutionary biology. Increasing evidence suggests that epigenetic modifications can vary within and between populations [1], but our knowledge of how epigenomes evolve by neutral and selective forces, and consequently their capacity to reveal population demographic histories is limited. DNA cytosine methylation, a conserved epigenetic modification in eukaryotes [2], occurs in plants within three sequence contexts: CG, CHG, and CHH (H represents A, T, or C) [3]. DNA methylation is known to be involved in regulating gene expression, suppressing transposable element activity, and stabilizing the genome [3]. Long-term changes in the methylome are mainly shaped by genomic alterations such as the proliferation of transposable elements and mutations affecting DNA methylation pathways while heritable stochastic epimutations that occur independent of genomic backgrounds drive short-term change [4].

The unique characteristics of epimutations make them an appealing marker for evolutionary investigations. In plants, CG methylation is maintained during cell division by METHYLTRANSFERASE 1 (MET1) [3]. Spontaneous stochastic loss or gain of methylation at CG sites can be transmitted stably across multiple generations [5]. Van der Graaf *et al*. have

estimated the forward (gain of DNA methylation) and backward (loss of methylation) epimutation rates per CG site in the model plant *Arabidopsis thaliana* to be approximately 2.56×10^{-4} and 6.3×10^{-4}, respectively, per generation per haploid methylome [6]. These rates are several orders of magnitude higher compared to the mutation rate of 7×10^{-9}, base substitutions per site per generation in the same population [7]. The increased rates of change at the epigenetic level may facilitate evolutionary inference over recent timescales, where the utility of slower-evolving genetic markers is limited [8, 9].

As transiently induced epimutations can be mistaken for stably inherited markers, a recent study exposed genetically identical *A. thaliana* to various environmental conditions to identify genomic regions—termed clocklike regions—where CG divergence rates are independent of environmental stimuli [10]. While these regions are valuable for evolutionary studies, they are challenging to identify in most species. Therefore, the same study observed that gene body methylated regions (gbM) exhibit a similar pattern of CG divergence as the clocklike regions [10]. gbM refers to a subclass of genes that display elevated CG methylation. They are mostly found in moderately and constitutively expressed housekeeping genes [11]. As they can be identified based on the distribution of methylation in the gene bodies, their usage opens the chance to investigate evolutionary processes in non-model plant species.

Previous attempts to explore how methylation variants evolve have either neglected demographic (neutral) models, mixed environmentally sensitive and insensitive methylation sites, or did not adequately assess the interdependence of genetic and methylation variants. Charlesworth and Jain's analytic framework for hypermutable sites [12] has been applied to create a methylation site frequency spectrum (mSFS) [4]. Previous studies generated mSFS for genic CG sites and the methylation states of gbM genes, finding either no selection or only weak selection acting on the methylome in *A. thaliana* [4, 13] and maize [14]. However, these studies do not incorporate an explicit demographic model while assessing selection. Another study found that positive selection acted on methylation variants linked to metabolite regulation in *A. thaliana*, even after accounting for demographic histories [15]. Other research in *Brachypodium distachyon* [16], *Fragaria vesca* [17, 18], lettuce [19], and grapevines [20] has compared evolutionary inferences using genetic and methylation variants by analyzing all CG sites as the environmental sensitivity of individual sites is unknown in most plant species. Recently, Sellinger *et al*. utilized methylation as a secondary marker alongside genetic variants to enhance demographic inference over short and long timescales [8]. The conceptual novelty was to consider that the underlying genealogy at a locus (i.e. the coalescent tree tracing back the ancestry of the sample back in time) is common for SNPs and SMPs (under a neutral model of evolution). This represents the first population genomics inference model combining DNA mutations, epimutations, and recombination along the genome, and the basis to develop a Sequential Markovian Coalescent method (SMCm). However, that study exhibits a fair amount of noise in the inference of the past evolutionary history when applied to methylome data from *A. thaliana* [8]. These inaccuracies are due to a lack of knowledge about the optimal SMP markers to use, the relevant genomic context, the relationship between SNPs and SMPs, and the SMCm method being very sensitive and not accounting well for methylated region effects (so-called differentially methylated regions or DMRs). A related question is whether DMRs can be also used for evolutionary inferences.

In light of these limitations, our goal was to assess how well methylation variants reveal known evolutionary patterns inferred using genetic variants. We chose *A. thaliana* and *B. distachyon*

for our analyses because their evolutionary histories are well-described [16, 21]. We found that the capacity of methylation variants to differentiate populations is contingent on when populations diverged. We also show that CG sites across the methylome capture within- and between-population patterns comparable to environmentally insensitive sites (clocklike regions and gbM) [10] in samples grown in a common garden. We found weak or no local correlations between genetic and methylation variants, indicating they reflect different aspects of population evolutionary histories. Additionally, the linkage between neighboring methylation variants was minimal, affirming their utility as independent markers for evolutionary studies. Conventional genome-based demographic inference methods, like the Sequential Markovian Coalescent [22], do show limitations in using methylation variants due to high sensitivity to violations of the Markovian properties of the underlying coalescent model along the genome [8]. Moreover, since such methods require knowing the variant accumulation rates and distributions—often unknown for methylation in many species—we developed a deep learning method that uses methylation as a neutral marker to estimate past demography. Unlike conventional convolutional networks, we use (to our knowledge) the first Encoder-Only Transformer architecture [23-25] method, focusing on the placement of mutations on a hidden ancestral recombination graph. We track coalescent events in a time-discretized transition matrix, then apply a coarse-grained approach, similar to tsABC [22], using heterogeneous sites per genomic window as input. By aligning training and real data distributions, we show that rapidly changing methylation variants can reveal recent demographic shifts in selfing and clonal species.

Results

CG methylation variants have variable performance in identifying population structure

We analyzed genetic and methylation diversity using 63 samples each from the Central European (CEU) and the Iberian non-relicts (IBnr) *A. thaliana* populations (Table S1). These populations were defined in [22]. Across the two populations, 31-33% of CG methylation sites in clocklike regions were polymorphic (Figure S1A), which is similar to a previous estimate for CG sites in *A. thaliana* [26]. In contrast, 1.6-1.7% of coding sites and 2.7-2.8% of non-coding sites were polymorphic (Figure S1A). We compared our results from *A. thaliana* with those from 29 samples from the clonally propagating grass *B. distachyon*. Wilson *et al*. used SNPs to identify clonal groups among Turkish *B. distachyon*, with samples within each group showing high levels of genetic similarity [27]. Eichten *et al*. identified high levels of consistency between the known genetic relationships for the clonal groups and the extent of CG divergence [16]. Here, we restrict our focus to SMPs and DMRs occurring within gbM regions and two clonal groups of *B. distachyon* with average bisulfite sequencing depths greater than 10 [16] (Group 1: 22 samples, Group 6: 7 samples) (Table S1). Between 4-7% of CG methylation sites within gbM regions were polymorphic in *B. distachyon* (Figure S1B). The median length of DMRs in *B. distachyon* was 34 bp (1st percentile: 16 bp, 99% percentile: 130 bp) which is smaller than the median length in *A. thaliana* DMRs, which was 181 bp (1st percentile: 78 bp, 99% percentile: 1125 bp) (Figure S2).

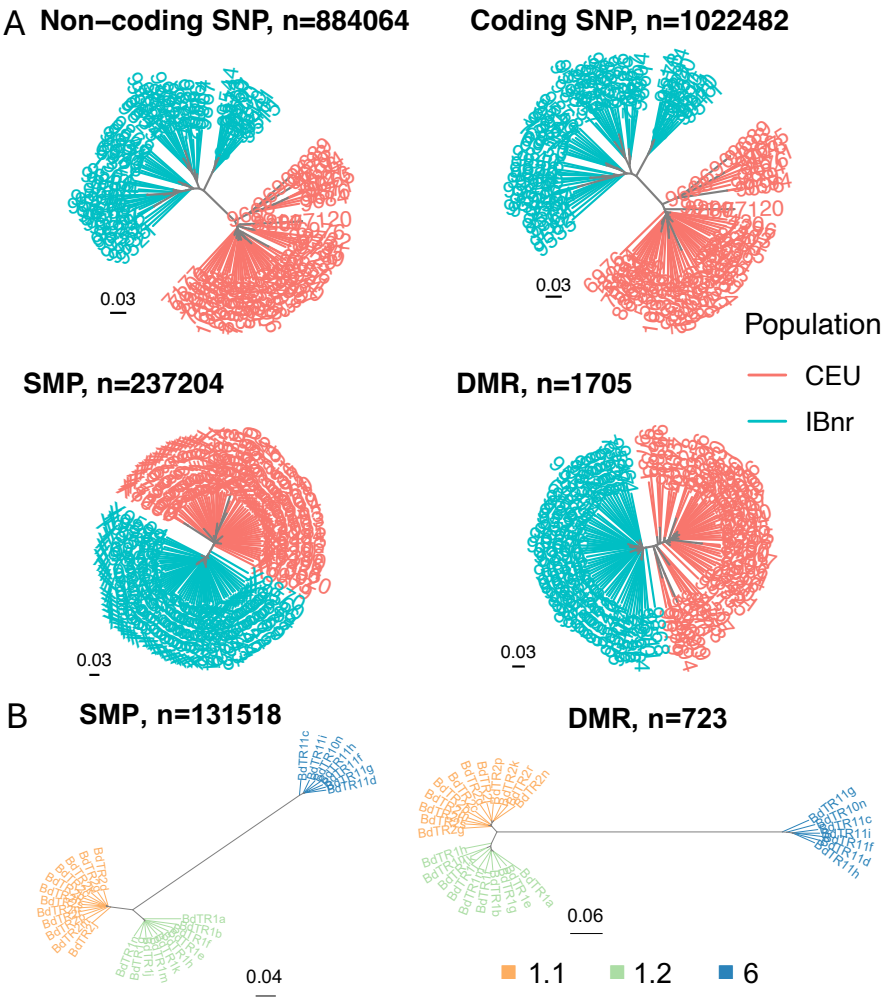

Figure 1. Methylomes outperform genetic variants in detecting population subdivision in *Brachypodium distachyon* but not *Arabidopsis thaliana*. (**A**) Neighbor-joining trees were generated using p-distance matrices for non-coding single nucleotide polymorphisms (SNP), coding SNPs, clocklike region single methylation polymorphisms (SMP), and clocklike region differentially methylated regions (DMR) for Central European (CEU) and the Iberian non-relicts (IBnr) *A. thaliana*. (**B**) Neighbor-joining trees generated using p-distance matrices estimated for SMP and DMR in gbM regions of Turkish *Brachypodium distachyon* clonal groups.

We estimated the proportion of sites at which two samples are different (p-distance) and clustering to uncover how the net total of genetic and methylation variation differed between samples from the CEU and IBnr populations. In this approach, a clear separation between the CEU and IBnr populations was apparent with both coding and non-coding single nucleotide polymorphisms (SNP) (Figure 1A). Although single methylation polymorphisms (SMP) and differentially methylated regions (DMR) largely separated the two populations, some samples were separated by only minimal distances (Figure 1A). Clustering indicated there were nine or more groups within the SNP data (Figure S3A-B) whereas only two groups were apparent in the SMP and DMR datasets (Figure S3C-D).

Furthermore, we performed discriminant analysis of principal components (DAPC) analyses to identify how correlated changes in subsets of genetic and methylation variants can be used

to discriminate the two populations. DAPC indicated greater discriminatory power with coding and non-coding SNPs compared to SMPs and DMRs (Figure S3E). Although p-distance matrix-based comparisons could have been influenced by the greater number of SNPs (Figure 1A), marker numbers were comparable for the DAPC, and yet SMPs and DMRs showed poor discriminatory capability (Figure S3E). SMPs and DMRs that occur within gbM genes have comparable performance to those occurring within clocklike regions in discriminating the two populations (Figure S4). High methylation rates in *A. thaliana* may have caused multiple changes at the same site (so-called homoplasy accounted for as a finite site model [4, 12, 28]), resulting in the underestimation of the true levels of divergence.

We then performed a similar analysis using the *B. distachyon* accessions. In contrast to the clonal grouping based on the genetic profiles [27], SMPs and DMRs were capable of additionally distinguishing the two subgroups of Group 1 (Figures 1B, S5). The trees estimated using the p-distance matrices were shorter for SMPs compared to DMRs (Figure 1B), possibly due to increased error in this dataset because of the shallow bisulfite sequencing depths. However, both trees were longer compared to those in *A. thaliana* (Figure S4A) indicating greater methylome differentiation in *B. distachyon*. Both our results using gbM regions and the results from Eichten *et al*. that use the entire collection of CG sites [16] reveal a difference in methylation profiles between the two subgroups of Group 1. We obtained phenotype data for the two subgroups [29] and found significant differences in the longitude (Figure S6), elevation of collection site, seed lengths, widths, yield production, and germination percentages (Figure S7). Our findings suggest that methylation variants can reveal subpopulation structure in recent timescales, where there has been little time for genetic differences and multiple methylation changes to accumulate.

Genomic contexts have little influence on the shape of SMP distributions

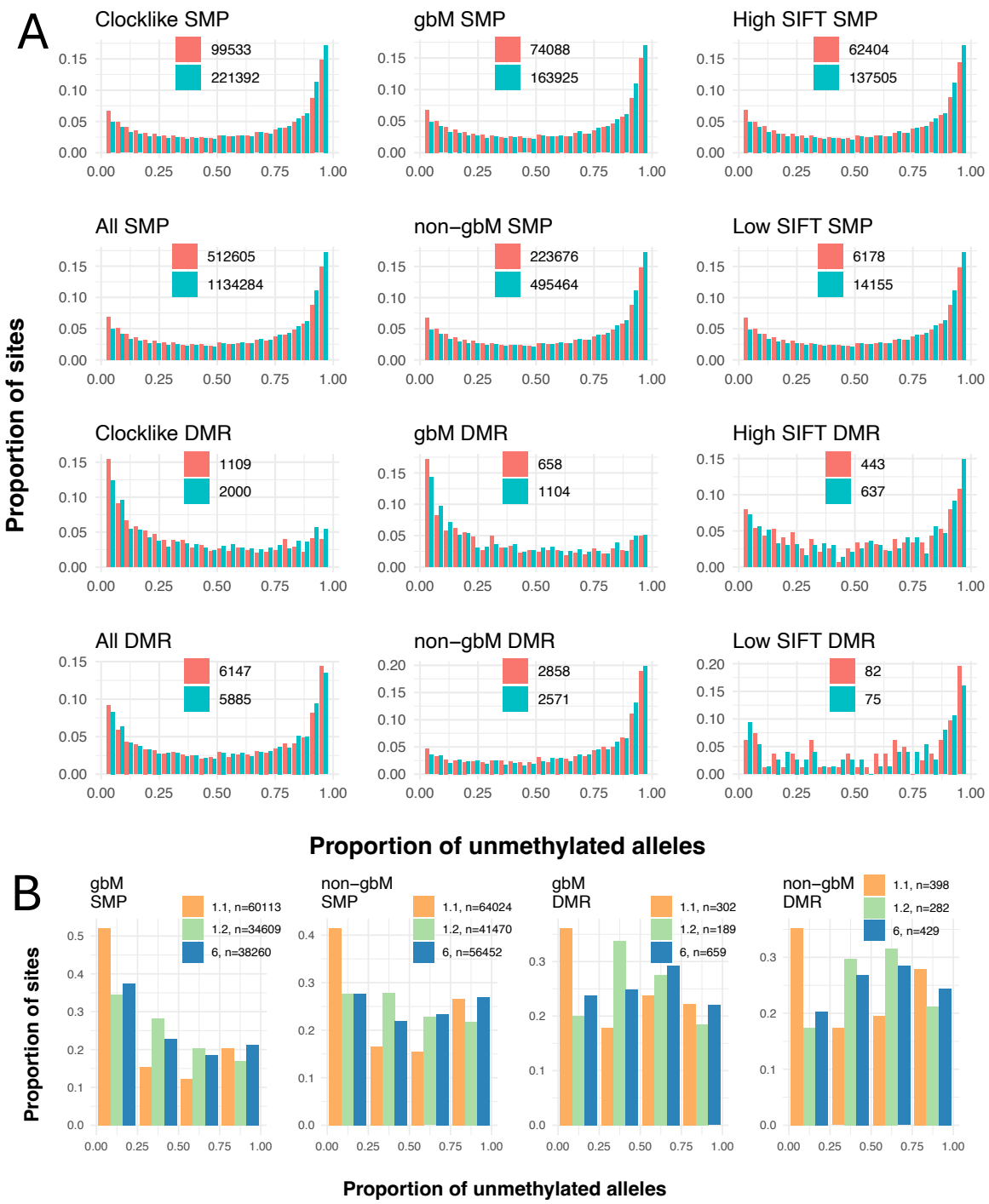

Figure 2. Methylation site frequency spectra (mSFS) generated using single methylation polymorphisms (SMP) were similar regardless of regional contexts, whereas mSFS generated using differentially methylated regions (DMR) exhibited greater variability. (**A**) mSFS for the Central European (CEU) and the Iberian non-relicts (IBnr) *Arabidopsis thaliana* populations using CG sites that occur in clocklike, gene body methylated (gbM), non-gbM, and low and high Sorting Intolerant from Tolerant (SIFT) score regions. Only sites with minor allele frequencies (MAF) >0.02 were used to generate the mSFS. (**B**) mSFS for *Brachypodium distachyon* clonal groups 1.1, 1.2, and 6 for SMPs and DMRs occurring within gbM and non-gbM regions. Only sites with minor allele frequencies (MAF) >0.04 were used to generate the

mSFS. For (A) and (B), the numbers in each panel indicate the number of sites used for the analyses.

We sought to understand how genomic contexts influenced the methylation site frequency spectra (mSFS) in *A. thaliana*. The mSFS reveals how methylation rates, demographic changes, and natural selection influence changes in the methylome over time [4, 12]. We found a greater frequency of unmethylated alleles at most polymorphic methylation sites for the CEU and IBnr populations, but CEU consistently had higher frequencies of unmethylated alleles (Figure 2A). The shapes of the mSFS for SMPs are consistent with previous findings that the backward methylation rate promoting the change from methylated to unmethylated was higher than the forward rate [6] and are consistent with previous mSFS generated by combining *A. thaliana* samples from extended geographic regions [4, 13]. The shape of the mSFS for SMPs in clocklike and gbM regions were similar supporting their interchangeability. We also studied the mSFS for intervals containing genes with low and high Sorting Intolerant From Tolerant (SIFT) scores which are positively correlated with the level of evolutionary constraint that genes are under [30]. Our results indicate that the level of gene constraint has little impact on the mSFS shape (Figure 2A).

When compared to SMPs, the DMR mSFS for *A. thaliana* were more dependent on the underlying set of intervals used to generate them. For DMRs that occur in intervals containing non-gbM genes, and high and low SIFT-score genes, more samples have the unmethylated state reflecting the underlying SMP distributions (Figure 2A). This is also true when DMRs across the entire genome are analyzed (Figure 2A). In contrast, for DMRs in clocklike regions and gbM genes, more samples show the methylated state (Figure 2A). This differences in the shapes of the SMP and DMR mSFS for these two classes of variants suggests that variable methylation states do not occur at the same sites within the DMRs.

In contrast to the mSFS for SMPs in *A. thaliana* (Figure 2A), the mSFS for all three clonal groups of *B. distachyon* indicated an excess of methylated alleles within the gbM for both SMPs and DMRs (Figure 2B). This same pattern holds for the mSFS for SMPs in non-gbM regions but there was less consistency in the shapes of the mSFS for DMRs in non-gbM regions (Figure 2B), similar to our observation when analyzing *A. thaliana* DMRs (Figure 2A).

Methylation and genetic variants show unique evolutionary signatures in *A. thaliana*

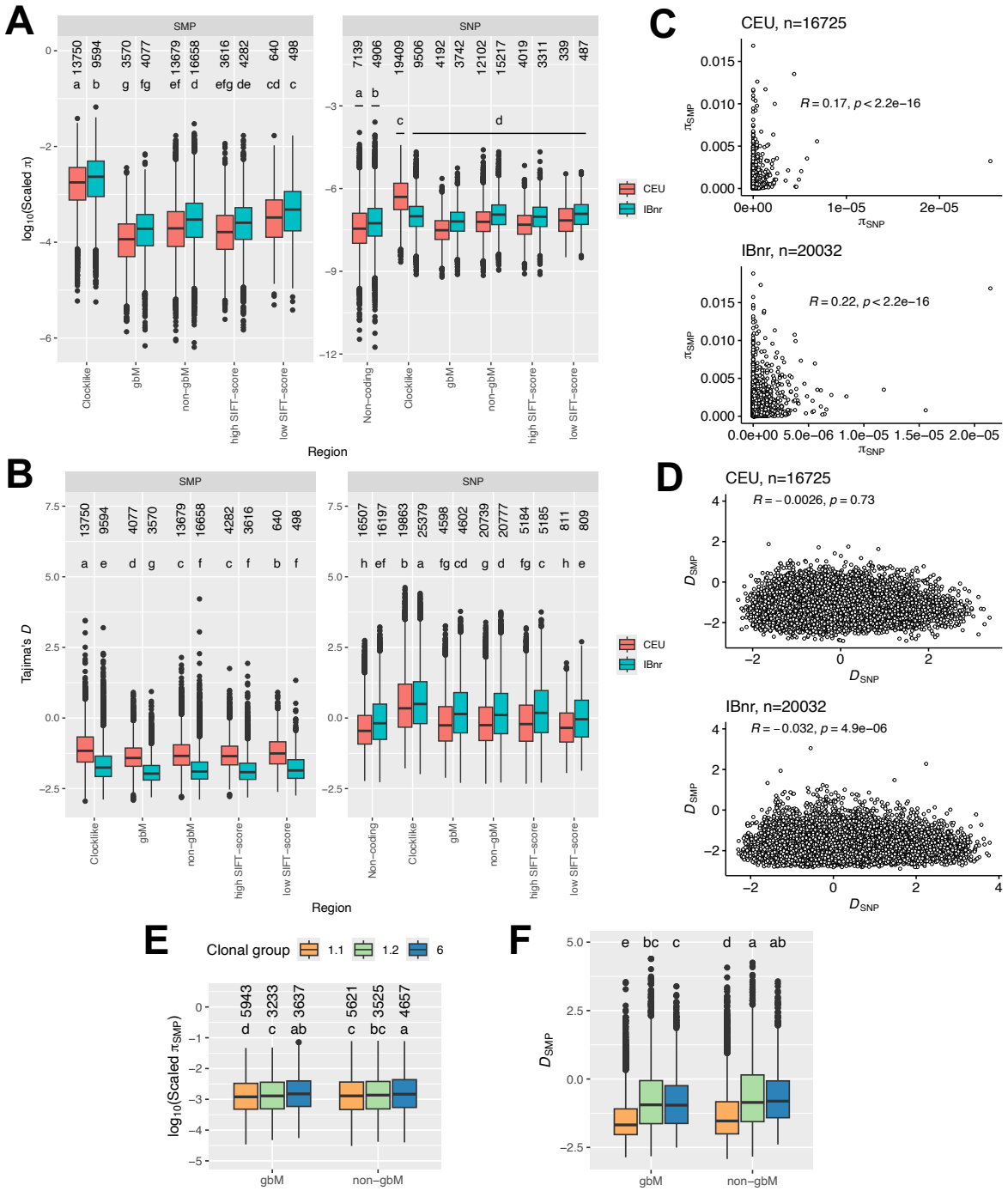

Figure 3. Unique evolutionary signatures in genomes and methylomes. (**A**) Estimates of pairwise nucleotide diversity (π) scaled by the number of cytosines per region for single methylation polymorphisms (π_{SMP}) and the number of bases for single nucleotide polymorphisms (π_{SNP}) for the Central European (CEU) and the Iberian non-relicts (IBnr) *Arabidopsis thaliana* populations. (**B**) Estimates of Tajima's *D* per region for CEU and IBnr. Comparisons of (**C**) π_{SNP} versus π_{SMP} and (**D**) Tajima's *D* for SNPs (D_{SNP}) and SMPs (D_{SMP}) per gene for CEU and IBnr. The numbers in the titles of each panel indicate the number of sites used for the analyses. Correlation tests were conducted to assess the associations between π and Tajima's *D*. (**E**) π_{SMP} scaled by the number of cytosines per region for *Brachypodium distachyon* clonal groups 1.1, 1.2, and 6. (**F**) D_{SMP} per region for *B. distachyon*. For (A), (B), (E), and (F), the numbers above the boxplots indicate the number of intervals.

Letters indicate group-wise differences in means following Tukey's honest significant difference tests. For (F), the color scheme and number of sites are the same as in (E).

We next sought to understand how genetic and methylation polymorphisms are distributed within *A. thaliana* populations. We first calculated the pairwise nucleotide diversity (π) for SMPs (π_{SMP}) and SNPs (π_{SNP}) from noncoding, clocklike, gbM, non-gbM, and high and low SIFT genic regions. We scaled estimates by the total number of sites (polymorphic and monomorphic) to ensure the results are comparable (that is per site estimates). π_{SMP} is three orders of magnitude higher than π_{SNP} (Figure 3A), likely driven by the high rates of change in methylomes [6]. π_{SNP} in the CEU population and π_{SMP} in CEU and IBnr populations for clocklike regions was significantly higher than in other regions (Figure 3A), possibly indicating better detection of environmental insensitivity with more polymorphic sites. π_{SMP} was higher for gbM and high-SIFT genes than at non-gbM and low-SIFT, respectively, but no such difference was seen for π_{SNP} (Figure 3A) indicating that constraint at the genic level has a minor effect on the levels of local methylation diversity.

We then compared how selective and demographic processes influence genomes and methylomes by estimating Tajima's *D* for CEU and IBnr. For methylomes, we used a modified Tajima's *D* using the D^m [28] that accounts for the hypermutability of the methylation sites. D_{SNP} was slightly negative for noncoding sites in the CEU and IBnr populations (Figure 3B), reflecting the known history of population expansions [22]. The higher D_{SNP} for IBnr (Figure 3B) is consistent with larger effective population sizes over recent timescales [22]. In contrast, IBnr had significantly lower D_{SMP} compared to CEU (Figure 3B). This could be due to variation in methylation rates, purifying selection, or demographic histories. Therefore, we used SMCm [8], which employs fixed mutation rates and compares the distributions of mutation and methylation markers, to estimate the forward and backward methylation rates for the IBnr and CEU populations. Methylation rates were only slightly higher in CEU but the ratio of backward to forward rates was similar in both populations (Figure S8). Hypermutability should result in greater frequencies of intermediate variants [12], but we did not observe such a pattern (Figure 2A). Tajima's *D* is based on a comparison of the number of segregating sites versus π. The disparity in D_{SMP} appears to be primarily driven by the variation in the number of segregating sites per region (Figure S9). IBnr exhibited 2.3 times more genotyped methylated sites compared to CEU (Figure S1A), suggesting a potentially greater capability to detect regions with low Tajima's *D* in this population.

We then estimated Tajima's *D* in different genomic contexts for CEU and IBnr. Clocklike regions had significantly higher D_{SNP} and D_{SMP} compared to other regions (Figure 3B). The D^m [28] method assumes forward and backward methylation rates are equivalent. Although the ratio of backward to forward methylation rate in clocklike regions is 1.36, that ratio is 2.11 and 2.84 for gbM and non-clocklike regions, respectively [10], meaning the assumption of D^m is less strongly violated for clocklike regions. D_{SMP} for non-gbM regions was slightly but significantly higher compared to the estimates for gbM regions (Figure 3B) suggesting that ignoring the differences between regions can introduce minimal noise when inferring evolutionary signatures from methylomes. Differences in D_{SMP} between high-SIFT vs low-SIFT were not consistent in both populations (Figure 3B). There was only a weak negative correlation for π (Figure 3C) generated for SNPs vs SMPs that occur in coding regions and no significant correlation for Tajima's *D* (Figure 3D).

We compared π and Tajima's *D* for *B. distachyon* SMPs to estimates generated using SNPs for the Anatolian and Turkish lineage (B_East) [31, 32] to which all three clonal groups belong. Scaled π for SMPs was larger for the *B. distachyon* clonal groups compared to the *A. thaliana* populations, but there were no consistent differences between gbM and non-gbM regions or among clonal groups (Figure 3A, 3E). Similar to *A. thaliana* (Figure 3A), scaled π for SMPs in all three clonal groups was three orders of magnitude larger than the median SNP-based scaled π (~1.8×10^{-6}) for the B_East lineage [31, 32](Figure 3E). Similar to *A. thaliana* (Figure 3B), D_{SMP} in the three clonal groups was negative. D_{SMP} was slightly but significantly larger in non-gbM regions compared to gbM regions (Figure 3F). These negative values contrast with the positive D_{SNP} for genetic variants in the B_East lineage [31]. Unlike in *A. thaliana* (Figure S9), this contrast cannot be attributed primarily to the differences in the number of segregating sites (Figure S10), meaning it cannot be explained solely by the extent of genotyping D_{SMP} was lower for Group 1.1 compared to the other two groups (Figure 3F) consistent with the higher frequency of rare alleles in this group (Figure 2B).

Linkage disequilibrium quickly erodes for methylation variants

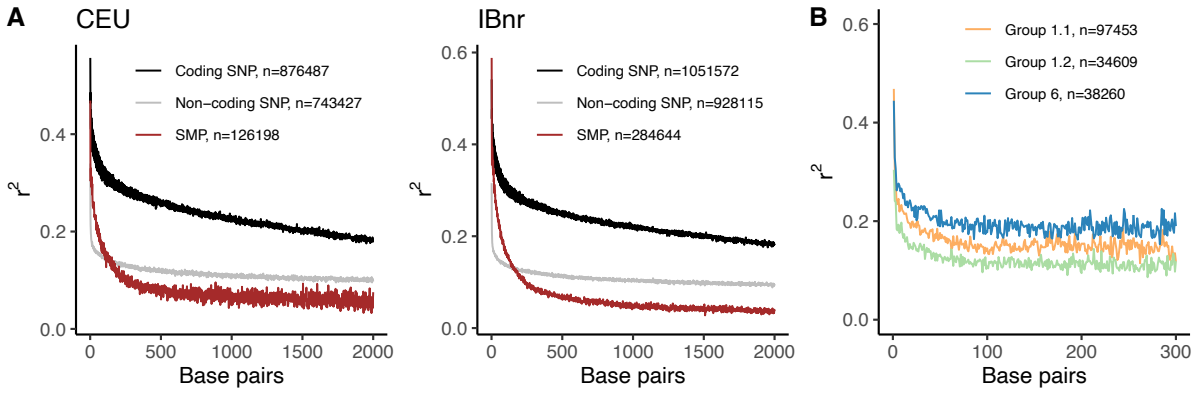

Figure 4. Weak linkage disequilibrium (LD) between neighboring single methylation polymorphisms (SMP). (**A**) Pairwise r^2 estimated using coding single nucleotide polymorphisms (SNP), non-coding SNPs, and SMPs for Central European (CEU) and Iberian non-relicts (IBnr) *Arabidopsis thaliana* populations. The number of sites used for comparisons is indicated within the plots. (**B**) Pairwise r^2 was estimated using SMPs for the clonal groups. For (A) and (B), the number of sites used for comparisons is indicated within the plots.

An important consideration for population genetic analysis is the presence of sites with independent evolutionary histories [8]. Therefore, we assessed levels of pairwise linkage disequilibrium (LD) to identify the number of independent polymorphic SNPs and SMPs. Pairwise LD decay was stronger for noncoding SNPs compared to coding SNPs in *A. thaliana* (Figure 4A). However, LD decay was much stronger for SMPs than SNPs with r^2 dropping below 0.1 within the first 250bp (Figure 4A). LD decays to 0.1-0.25 for SMPs sites within gbM regions for *B. distachyon* within the first 100 bp but remains constant thereafter (Figure 4B) and is stronger compared to LD in *A. thaliana* over large distances (Figure 4A).

Demographic inference using genetic and methylation variants

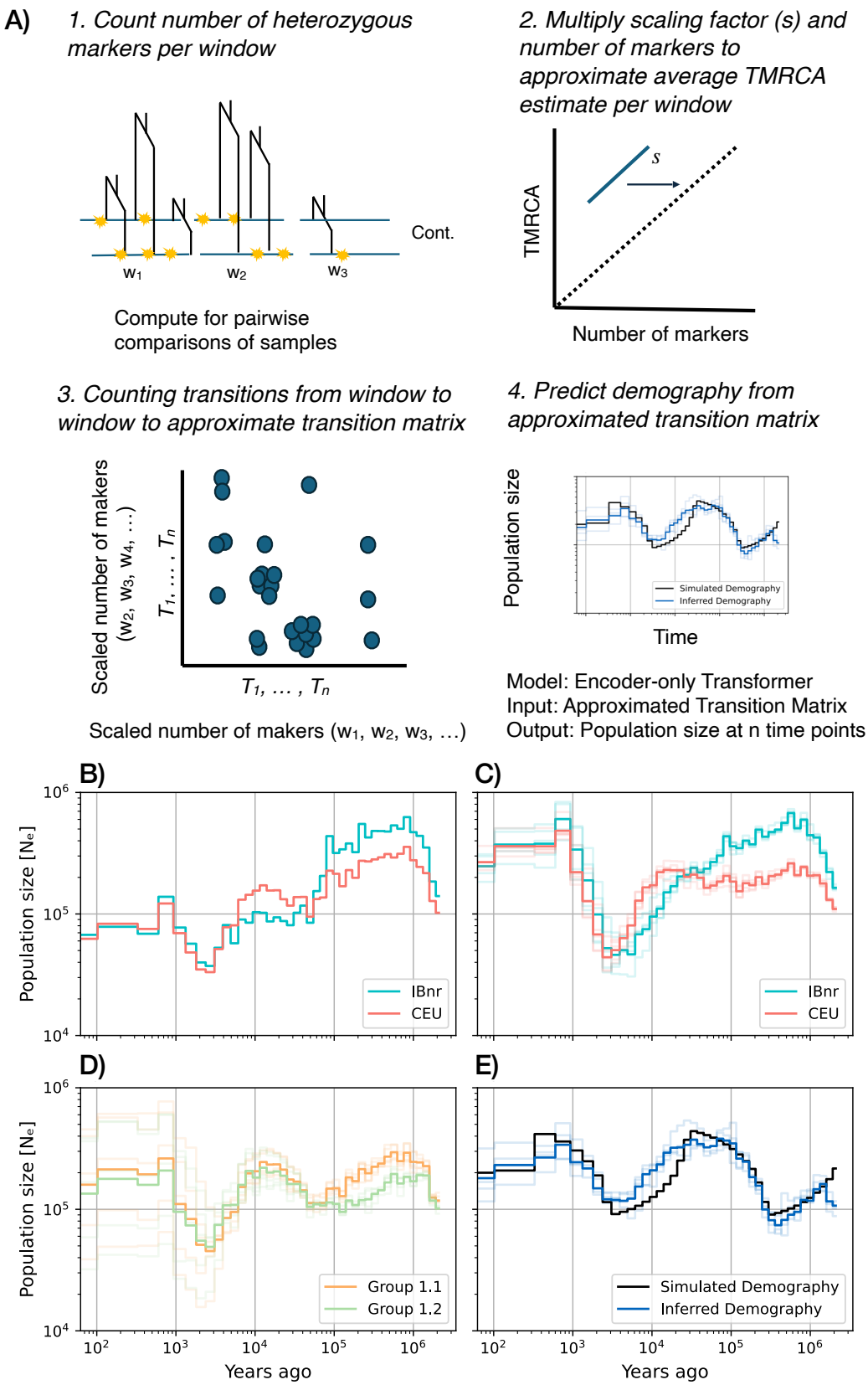

Figure 5. Demographic inference using mutation or methylation markers. **(A)** Schematic of the approximated transition matrix inference framework. The genome is first divided into

20Kbp bins, and heterozygous markers are counted for all pairwise comparisons in a sample of 10 individuals. These counts are then scaled by an empirically chosen factor to ensure sufficient values in the approximated transition matrix. The framework constructs this matrix by concatenating all pairwise comparisons into a long sequence and applying a sliding window of size 2 and step size 1. Each pair of consecutive values in this window represents coordinates in the transition matrix, which is incremented at those positions. This process results in an unnormalized transition matrix that captures the genetic relationships between samples. Finally, an encoder-only transformer neural network takes this noisy matrix as input, implicitly learning the fixed scaling factor, and predicts population sizes at various time points. Inference using over 42 time steps using (**B**) single nucleotide polymorphisms (SNP) and (**C**) single methylation polymorphisms (SMP) for the central European (CEU) and the Iberian non-relicts (IBnr) *Arabidopsis thaliana* populations. (**D**) Demographic inference using SMP for Groups 1.1 and 1.2 of *Brachypodium distachyon*. SMP inference was done using sequences from all five chromosomes (light lines, average in bold), while SNP inference is based on chromosome one. (**E**) Inference of simulated sawtooth demography using five replicates, 4Mbp segments, and 10 samples.

We developed a novel inference method that focuses on large genome blocks (20kb windows) likely spanning multiple coalescent genealogies (Figure 5A), to estimate the times to the most recent common ancestor (TMRCA). Our method assumes the number of heterozygous markers per window to correlate with the average TMRCA. Essentially, longer coalescent times allow more mutations and epimutations to accumulate. To mitigate the possibility that older genealogies (long TMRCA) can be unexpectedly short due to immediate recombination, our approach uses 20kb windows to average out genealogies. We apply a scaling to the number of markers to estimate TMRCA (Figure S11). Although the chosen scaling factor will not perfectly offset all variable demographic samples—given that we trained using a fixed recombination rate and a fixed window size—offsets are minimal and addressed during training. An encoder-only transformer neural network processes this data, learning the scaling factor and predicting population sizes over time. This is done by summarizing the TMRCA of two consecutive windows in the empirical transition matrix. The differences between each pair of samples are used to infer their TMRCA. The TMRCA values for all pairs across multiple intervals in the genome are then represented as a transition matrix. This method combines raw genotype data restructuring with deep learning to infer demographic history.

For deep learning inference, the distribution of heterozygous markers in training and real data must overlap to ensure in-distribution inference. For the training data, we collapsed each training transition matrix into a single scalar by summing the flattened matrix and plotted the distribution of unnormalized transition matrices (Figure S12A). To ensure the real data *from A. thaliana* and *B. distachyon* matched the training data, we analyzed 20 randomly sampled genomic regions. For SNP data, we selected start positions uniformly between 0-28 Mbp, while for methylation data, start positions were chosen uniformly between 0-0.5 Mbp. For both data types, we determined each region's length by sampling from a uniform distribution between 1-3 Mbp. Summing the resulting transition matrices for the IBnr, CEU, Group 1.1, and Group 1.2 regions (Figure S12B-D) produced values within the training data range (Figure S12A). Despite the differential properties of SMPs and SNPs, the distribution of heterozygous markers per 20 Kbp window was similar across populations (Figure S12B-C), supporting the use of a common training dataset for deep learning.

We applied our coarse−grained inference approach to *A. thaliana* and *B. distachylon*. We generated approximated transition matrices from ten samples and four Mbp sequence lengths. The 45 pairwise comparisons totaling 180 Mbp with 20 Kbp windows yielded 9,000 pairs of TMRCA values per matrix. We detected a population bottleneck ~100,000 years ago (100 kya) in CEU and IBnr using SNPs (Figure 5B), consistent with a previous study [22]. This signal was not clearly detected with SMPs (Figure 5C), indicating their limited use for ancient events. Both SNPs and SMPs indicated another bottleneck between 1-10 kya (Figure 5B-C), but SMPs also revealed a subsequent population expansion (Figure 5C) undetected by SNPs (Figure 5B). Using SMPs, we recovered two bottlenecks (~100 kya and between 1-10 kya) in *B. distachylon* (Figure 5D) that were previously reported using SNPs for samples combined from multiple clonal groups in this species [31]. The steeper expansion of IBnr compared to CEU (*A. thaliana*) and Group 1.1 compared to Group 1.2 (*B. distachyon*) in the last 10,000 years likely led to the proliferation of rare alleles (Figures 2B, 3F).

We validated our demographic inference with two approaches. First, we simulated the sawtooth demography observed in both species, confirming that our deep learning method accurately detects multiple bottleneck and expansion events (Figure 5E). Second, we simulated methylation markers with high rates of change (10^{-4}, 10^{-5}, or 10^{-6} per site per generation) and backward rates 2.5 times larger than forward rates, based on the estimates provided in [6], to test if deviations from the infinite sites model affect inference. We found that our method accurately recovered demographic histories beyond 0.6 kya and before 5, 22, and 442 kya for methylation rates of 10^{-4}, 10^{-5}, and 10^{-6} per site per generation, respectively (Figure S13). This suggests that inferences 20 kya and beyond are unlikely to be accurate for CEU and IBnr due to their estimated rates of methylation change being around 10^{-5} per site per generation (Figure S8). Thus, the recent population expansion observed with SMPs (Figure 5C) highlights the potential of methylation markers to reveal insights beyond what genetic variants alone can provide.

Discussion

We observed contrasting patterns in the capacity of methylation variants to distinguish population subdivisions in *A. thaliana* and *B. distachyon*. In *A. thaliana*, the infinite sites model is likely violated for methylation, resulting in the erosion of methylome differentiation. In *B. distachyon*, samples from different altitudes with varying seed morphology exhibited distinct methylation profiles in a common garden, despite their genetic similarity. While SMP distributions are similar across different genomic contexts, DMRs are more context-dependent, making the former preferable for population-scale analyses. We found weak negative correlations between π and no local correlations for Tajima's *D* between genetic variants and methylation variants in *A. thaliana*, underscoring their distinct molecular and evolutionary properties and the difference of resolution at different time scales. Recombination appears minimal between neighboring methylation variants, affirming their utility as independent markers for population-level inferences using local genealogies along the genome. SMPs and SNPs recover recent and older demographic changes, respectively, providing a comprehensive reconstruction of population evolutionary histories.

484 The differing ability to detect population subdivisions in *A. thaliana* and *B. distachyon* using
485 methylation variants could lead to differences in divergence times, methylation rates, or local
486 adaptation. As the post-glacial re-colonization of the Iberian Peninsula and the spread
487 northwards started ~16 kya [33], multiple changes at the same methylation site during this
488 period may have caused an underestimate of the true levels of divergence in *A. thaliana*. The
489 greater capacity to detect group subdivision is *B. distachyon* could reflect altitude adaptation
490 contributing to methylome divergence, similar to what was found in *F. vesca* [17]. However,
491 given that we generated inferences using gbM regions that are highly conserved in
492 angiosperms [11], this seems unlikely. It could be due to lower rates of methylation change,
493 but we could not estimate methylation rates for *B. distachyon* as our rate estimate relies on
494 comparing the distribution of genetic and methylation variants. Another possibility is that the
495 two subgroups diverged recently. As the B_East lineage split from the western Mediterranean
496 lineage 23 kya [31, 32], the split between the closely related subgroups is likely to have been
497 far more recent, ensuring the infinite sites model was not violated for methylation variants. Our
498 findings underscore the necessity for methods distinguishing neutral demographic changes
499 from selective pressures on the methylome, elucidating why SMPs behave differently across
500 species.
501
502 Our results support the use of individual CG sites from all genomic contexts for population-
503 scale analyses. Our between-population comparisons using CG sites in gbM regions
504 successfully identified the known population structure within *B. distachyon*, similar to a
505 previous study using genic CG sites [16]. Further supporting this conclusion is the consistent
506 similarity in the mSFS shape when using SMPs, regardless of their genomic context. The *A.*
507 *thaliana* [21] and *B. distachyon* [16] methylomes, generated under similar environmental
508 conditions, ensure that sites affected solely by transient environmental effects would not be
509 recognized as SMPs. Another study using all CG sites from lettuce methylomes, cultivated
510 under uniform environmental conditions, also demonstrated the capacity to distinguish
511 multiple species [19]. Some noise can be introduced by analyzing the whole methylome as
512 non-gbM regions show a slight skew towards variants with intermediate frequencies, but this
513 is likely to be offset by the increased number of sites for inference. The distribution of DMR
514 states is tied to the genomic context. Studying DMRs can nevertheless be valuable for
515 imputing methylation states when sequencing depths are low [34]. Overall, using a restricted
516 set of CG sites may be more appropriate when analyzing accessions grown under variable
517 environments together or for tracking long-term methylome divergence [10].
518
519 The weak local correlations between genetic and methylation diversity and the association
520 between gene constraint and methylation diversity in *A. thaliana* can partly be attributed to
521 methylation affecting the mutability of neighboring sites [35-37] and transposable element
522 polymorphisms influencing methylation variation [38, 39]. However, only about 12% of
523 methylation quantitative trait loci (QTLs) in *A. thaliana* are within 10Kbp of the epiallelic target
524 [40]. In maize, approximately 50% of methylation QTLs occur in *cis* [41], indicating a potentially
525 stronger trend in this species. The higher rate of methylation changes compared to mutation
526 accumulation [6, 7] may also explain why methylation differences persist despite genetic
527 homogeneity. Our simulations also show that coalescent histories of markers with vastly
528 different rates of change diverge, which can explain the general lack of correlation between π
529 and Tajima's *D* for local genetic and methylation diversity. Our results are similar to a previous
530 study in lettuce that also found higher levels of polymorphism in the methylome compared to
531 the genome [19]. The lack of correlation or similarity between the Tajima's *D* estimates from

the genome and methylome in *A. thaliana* and *B. distachyon* supports the notion that the SNPs and SMPs likely reflect different parts of the common underlying coalescent genealogy at a locus: SNPs would reflect the older part of the tree, while SMPs would reflect the topology and branch lengths in the more recent past. It is then not surprising that for recent positive selection events (selective sweeps), the signatures are similar for both types of markers, and SMPs may even be more accurate to detect them [15]. Our study mostly focuses on local correlations in diversity, rather than genome-wide correlations, where life history traits and genetic differentiation levels also play a significant role [42-48].

The faster decay of linkage disequilibrium (LD) for methylation sites compared to SNPs is a known phenomenon, with SMP correlations halving within the first 500 bp in human populations [49]. We found slightly stronger linkage between neighboring SMPs compared to a previous estimate in wild *A. thaliana* sampled across the Northern Hemisphere [40], likely due to our focus on individual populations with less genetic structure [22]. Nevertheless, our finding of low levels of linkage between neighboring SMPs in *A. thaliana* and *B. distachyon* suggests that they are versatile markers for evolutionary analyses.

Our study demonstrates that methylation variants can independently detect and allow inference of historical demographic changes. This represents a significant improvement over a previous approach [8], where methylation was used only as a secondary marker to supplement genetic variant-based inferences. Furthermore, our improved deep learning method does not require precise methylation rate parameters and is less sensitive to the presence of invariant methylation sites (compared to the SMCm in [8]). Instead, it trains on diverse scenarios to match observed variant distributions. For *B. distachyon*, methylation variants revealed expansions also detected by genetic variants [31]. In *A. thaliana*, genetic variant-based demographic inferences fail to detect recent population expansions (this study and [50]), which can instead be uncovered through methylation variants. Out simulations confirmed the utility of rapidly changing markers for inferring demographic changes. Overall, our study highlights the value of methylation markers for understanding recent shifts in population size.

Conclusions

Our findings demonstrate that CG methylation can provide new insights into population structure in clonal and selfing species, similar to its previously demonstrated utility in *A. thaliana* from the Northern Hemisphere and the clonal seagrass *Zostera marina* [10]. We demonstrate the utility of methylation variants for uncovering very recent demographic events, where SNP markers are limited due to their slower rate of change. We also illustrate its usefulness in clonal groups, where the paucity of SNPs would render such inferences either impossible or necessitate very deep and costly levels of DNA sequencing. Conversely, at older timescales, methylation markers are unlikely to be informative because the high rates of change would have resulted in the violation of the infinite sites model. We show that SNPs and SMPs are complementary for generating demographic inferences over short and long timescales, highlighting the value of a recently developed method that leverages both sources of variation for inferring demography [8]. Our work demonstrates that methylomes contain unique evolutionary insights unattainable through studying genomic variation in isolation.

Methods

Genetic and methylation variant calling in Arabidopsis thaliana

We obtained the *A. thaliana* 1001 genomes [51] SNP calls from https://1001genomes.org/data/GMI-MPI/releases/v3.1/. We only retained biallelic SNPs for our analyses. As C/T variant calls can become confounded with methylation calls for data generated using bisulfite sequencing, we generated sample-specific genome references for mapping bisulfite sequencing reads. We substituted the genetic variant calls for each sample into the TAIR10 genome reference [52] using SAMtools [53], BCFtools consensus [53], and fastq split [54]. We obtained bisulfite sequencing data for the 1001 *A. thaliana* from [21]. We first removed poor-quality reads using Trimmomatic [55] with the following options: ILLUMINACLIP:TruSeq3-SE.fa:2:30:10 LEADING:3 TRAILING:3 SLIDINGWINDOW:4:15 MINLEN:36 for single-end reads and ILLUMINACLIP:TruSeq3-PE.fa:2:30:10:2:True LEADING:3 TRAILING:3 SLIDINGWINDOW:4:20 MINLEN:36 for paired-end reads. We subsequently mapped reads to the sample-specific reference genomes using Bismark with the aid of the hisat2 aligner [56]. We ran Bismark deduplicate_bismark to remove optical duplicates and ran bismark_methylation_extractor to extract methylation calls. We studied cytosine sites with a coverage of at least five reads similar to what was done in [21]. To identify the methylation state of a site, we performed a binomial test with the non-conversion rate being used as the hypothesized probability of success following the method in [57]. The non-conversion rate was calculated as the proportion of methylation in the chloroplast as done in [57]. Sites were assigned as methylated if the false discovery rate corrected *P*-values following the binomial test was less than 0.01. Otherwise, they were designated as unmethylated. We used jDMR [58] to identify DMRs in the CG contexts as the method accounts for coverage when calculating likelihood scores for methylation states. For this we called methylation status per site using METHimpute (function: callMethylationSeparate) [34], extracted cytosine clusters in the CG contexts ensuring there were a minimum of eight cytosines in each cluster (function: CfromFASTAv4 and makeReg with default options makeRegnull = c(FALSE), N.boot = 10^5, N.sim.C = "all", fp.rate = 0.01, set.tol = 0.01), and identified the methylation states of the regions in each sample (function: runMethimputeRegions) ensuring that we used a minimum of eight cytosines and a coverage of three.

63 IBnr and 67 CEU samples overlapped between the SNP and methylation variant call files. We randomly subsampled 63 samples from the CEU population to ensure the numbers were comparable to the IBnr population. For our analyses, we only used sites where at least 80% of samples within each population were genotyped. The proportions of variant SNP and SMP sites were calculated by dividing the number of sites with minor allele frequencies greater than 0.02 by total number of variant and invariant sites.

Population (epi)genetic metric estimation for Arabidopsis thaliana

To estimate π and Tajima's *D*, we created fasta files for each genomic region containing the sequences for each sample. We substituted the variants from the SNP vcf into the TAIR10 reference genome using the approach described previously for each sample, extracted the region of interest, and converted it to a fasta format. The regions could either be the clocklike regions described in [10], genic regions comprising all exons, or non-coding regions that

comprise of all regions other than exons. Genic regions were further split into gbM genes using the list for *A. thaliana* provided by [59] and high SIFT-score (>0.75) and low SIFT-score (<0.3) genes using the list provided by [60].

We estimated π_{SNP} and D_{SMP} using pegas [61] and estimated π_{SMP} and D_{SMP} using the D^m [28]. We only analyzed intervals that had at least three polymorphic sites and sequences with lengths greater than 10bp. We calculated the number of cytosines in each interval using METHimpute [34]. To compare π and Tajima's *D* among the different genomic contexts, we built a linear model where these metrics were the dependent variable, and the concatenated population and genomic context groupings were the predictor variables. We then applied a Tukey honest significant differences test using the agricole R package (https://myaseen208.com/agricolae//index.html) to identify significant differences between individual predictor levels. We performed a correlation test to compare the π and Tajima's *D* for SMPs and SNPs per exon.

We used VCFtools [62] to estimate the allele frequencies for SMPs and DMRs. We used PopLDdecay [63] to estimate pairwise LD using the r^2 metric analyzing all sites with a minor allele frequency greater than 0.005.

Between population comparisons for Arabidopsis thaliana

We combined the CEU and IBnr vcfs and used VCF2Dis (https://github.com/BGI-shenzhen/VCF2Dis) to estimate the p-distance matrix. We used this matrix to generate neighbor-joining trees using FastME [64] and plotted it using ggtree [65]. We also performed DAPC to discriminate samples from the CEU and IBnr populations. We thinned the dataset so that only sites that were separated by 1Kbp were sampled to reduce the computational time. We converted vcf files into a genlight format using the *genomic_converter* function in the R package radiator (https://thierrygosselin.github.io/radiator/). We used the find.clusters function in adegenet [66] to identify the number of clusters in each dataset allowing for a maximum of 20 clusters for SMPs/DMRs and 30 clusters for SNPs. As DAPC regions require fully typed data, we imputed missing values using the mean value. Then, we performed cross-validation using adegenet [66] to identify the number of informative principal components. We retained a maximum of 15 principal components, used 90% of the data for training, and calculated group-wise assignment success. We centered but did not scale variables. We used 30 replicates for each principal component. Finally, we performed DAPC using adegenet [66].

Methylation rate estimation *for Arabidopsis thaliana*

We generated the multihetsep files for SNPs for the same 5Mbp regions that were used for SMPs (described in the section immediately above). We combined the SNP and SMP multihetsep files. We randomly selected 20 samples from each population to ensure reasonable runtimes. We used the *Methylation_rate_estimation* function in SMCm to estimate forward and backward rates [8]. We set the mutation rate as 7×10^{-9} per site per generation and the recombination rate as 3.5×10^{-8} per site per generation. We ignored regional influences on methylation rates and estimated rates under a site-only model. We used the known estimates of forward (2.56×10^{-4} per generation per haploid methylome) and backward methylation rates (6.3×10^{-4} per generation per haploid methylome) for *A. thaliana* [6] as priors.

676
677 *Genetic and methylation variant calling in Brachypodium distachyon*
678
679 We obtained whole genome sequencing data (29 samples) for *B. distachyon* from [27] and
680 whole genome bisulfite sequencing data from [16]. We used Bd21-3 v1.2 genome reference
681 and the GenBank annotation from the Joint Genome Institute (http://phytozome.jgi.doe.gov/)
682 for variant calling. We used Trimmomatic [55] to trim reads using the paired-end options as
683 stated above for the whole genome sequencing data and the single-end option for the whole
684 genome bisulfite sequencing data. We mapped whole genome sequencing data reads to the
685 reference using bwa-mem [67]. We used Picard Toolkit (https://broadinstitute.github.io/picard/)
686 to add read groups and mark duplicate reads. We used SAMtools [53] to remove unpaired
687 reads, remove reads with mapping quality of less than 20, and sort reads. We called genetic
688 variants using GATK HaplotypeCaller [68]. We only retained SNPs with depths greater than
689 five and quality scores greater than 30 using BCFtools [53]. Using this SNP variant call file,
690 we perform methylation variant calling in the same way as was done for *A. thaliana*. We
691 obtained the sample localities from [29] and created a map showing their occurrence with Map
692 Maker (https://maps.co/).
693
694 *Within and between population analyses in Brachypodium distachyon*
695
696 We used a minor allele frequency threshold of 10% to identity polymorphic sites in each clonal
697 group due to the smaller number of samples being analyzed when compared to *A. thaliana*.
698 For the analysis of SMPs and DMRs, we only used variants that occurred within CG-gbM
699 regions identified in [69]. We estimated mSFS, LD, p-distance matrices, π, and Tajima's *D* in
700 a similar way as we did for *A. thaliana*. We thinned the SMP dataset so that only sites that
701 were separated by 3Kbp were sampled to reduce the computational time for the DAPC
702 analyses.
703
704 *Generating the approximated transition matrix for demographic inference*
705
706 We created a training and testing dataset consisting of a combined 60×10^3 simulations
707 (80%/20%, respectively). Of these 10×10^3 were constant demographies (*i.e.*, no demographic
708 change) with a random population size drawn between 10×10^3 and 200×10^3 and 50×10^3
709 random walk demographies, with time steps being defined for $i \in \{0,1,...,K-1\}$ using:
710

711 $$(\text{population_time})_i = \frac{\exp\left(\frac{i}{K-1}\cdot\ln(1+\delta t_{\text{max}})\right)-1}{\delta}$$

712
713 where K=42 is the number of time points, δ = 0.001 is the growth rate, and $t_{\text{max}} = 2.1\times10^6$ is the
714 maximum time.
715
716 The population size was drawn for each of the K=42 time points in the following way: an initial
717 population size was randomly selected between a minimum ($n\ min = 10\times10^3$) and maximum
718 ($n\ _max = 1.2\times10^6$) value. For each subsequent time point, a new population size was
719 proposed by multiplying the previous size by a random factor between 0.1 and 10. If this
720 proposed size fell outside the allowed range (*n min* to *n max*), new proposals were generated
721 until an acceptable value was found. This process was repeated for all 42 time points, resulting

in a sequence of population sizes that exhibit both gradual and abrupt changes while remaining within the specified bounds. Nevertheless, a sliding window average with size 6 and step size of 1 was applied to smooth extreme changes. This approach for sampling demographies has been adapted from [70].

The obtained population sizes and times were passed onto *msprime* [71] to simulate the corresponding ancestral recombination graphs using a recombination rate of 3.4×10^{-8} per base pair and generation. For SNPs, branches were mutated at a rate of 7×10^{-9} per base pair and generation, leading to a ρ over θ ratio of 4.86.

The approximated transition matrix was obtained from the genotype matrix (*GM*) with dimensions $n \times m$, where $n,m \in \mathbb{N}$ represent the number of samples and mutations, respectively. Each element g_{ij} of *GM*, where $i \in \{1,...,n\}$ and $j \in \{1,...,m\}$, denotes the presence ($g_{ij} = 1$) or absence ($g_{ij} = 0$) of mutation j in sample i. We generated a corresponding vector of positions of size m for each segregating site containing floating point numbers of the location in the genome.

For each random population size parameter, we used a genome of length 4Mbp,10 samples (ploidy=1), and the *GM* and positions vector to construct a density estimate of mutations along the genome (in theory corresponding to the respected TMRCA at that region). To ensure the presence of enough markers, we segmented the genome into 20Kbp pieces and counted the number of heterozygous markers between all pairwise $\binom{10}{2}$ combinations. The 4Mbp sequences of all comparisons were concatenated and scaled by the natural log. Likewise, the population time steps were also log-scaled. To make sure that the number of markers per window fell approximately into the time windows, we scaled the markers by an arbitrary chosen scaling factor ($=e^{8.2}$) (Figure S13). The importance of the given scaling factor is negligible, due to all the transformation steps occurring in the pre-training, and therefore any noisy representation presented to the learning algorithm will be part of the training.

Each *msprime* simulation (under a random demographic history) yielded one *approximated* transition matrix, which was obtained by counting the transitions (scaled number of heterozygous site in window t → window t+1) from one 20 Kbp window to the next using the following algorithm: a sliding window of size 2 and step size 1 was applied along the sequence and each pair of consecutive values in this window represents coordinates in the transition matrix, which was incremented at those positions leading to a filled matrix which remained unnormalized. Lastly, the entire transition matrix was incremented by one at each entry and scaled by the natural log to squeeze all values approximately into the same range to avoid training instability.

Model description, training, and inference

The inference approach can be described as a supervised learning approach using the *approximated* transition matrices x with defined dimensions $\mathbb{R}^{L=42\times K=42}$ as the input and the population size at each time step as the predicted variable. The input is a square matrix where both dimensions (K and L) are 42. The model architecture is an encoder-only transformer [72] (https://github.com/lucidrains/x-transformers). It consists of three main components: an input

projection layer, a transformer encoder, and an output projection layer. It can be formalized as:

1. Input Projection: $x_{proj} = W_{in}x + b_{in}$, where $W_{in} \in R^{D_{enc} \times K_{in}}, b_{in} \in R^{D_{enc}}, x \in R^{L \times K_{in}}$

2. Transformer Encoder: $z = \text{Encoder}(x_{proj})$, where $z \in R^{L \times D_{enc}}$

The Encoder employs a configuration with dimension D_{enc} = 512, depth N_{enc} = 12, number of attention heads H_{enc} = 10 heads, Gated Linear Unit activation in feed-forward layers [73], residual attention connections [74], rotary positional embeddings [75].

3. Dimension Reduction: $z_{reduced} = \sum_{i=1}^{L} z_i$, where $z_{reduced} \in R^{D_{enc}}$

4. Output Projection: $y = W_{out} z_{reduced} + b_{out}$, where $W_{out} \in R^{D_{out} \times D_{enc}}, b_{out} \in R^{D_{out}}$

In this formalization, sequence length L = input dimension of transition matrix K_{in} = 42, representing the square input matrix of 42 x 42 dimensions, and output dimension D_{out} = 42.

The neural network model underwent training for 50 epochs, employing mean squared error as the loss function. The training process leveraged the Accelerate framework from Hugging Face to enhance performance [76]. An Accelerator object was configured with mixed precision using bfloat16 and gradient accumulation over 12 steps (with batch size 32). Throughout the training regiment, both the training and test losses were continuously monitored to evaluate model performance and assess convergence.

Generating data for demographic inference

We first generated unique variant call files for each sample from the population variant call files using BCFtools [53]. Then we used the generate_multihetsep.py from MSMC-tools (https://github.com/stschiff/msmc-tools/tree/master) to combine all the samples per chromosome. For *A. thaliana* SNPs, we used the entire chromosome 1 as we needed a long contiguous fragment to generate the approximated transition matrix. For SMPs, we used 5Mbp segments in each of the five chromosomes (Table S2) as the SMP density was far higher. We used the list of genotyped cytosine positions as a genomic location mask for the SMPs. For *B. distachyon*, we included singletons to support the demographic inference given the small sample sizes in this species. The data was polarized by identifying the minor (less frequent) alleles and encoding them as derived, while the major alleles were encoded as ancestral. The resulting genotype matrix represents this polarized, unphased data, where each row corresponds to an individual and each column to a genomic position.

Methylation simulation model

We explored the boundaries of our course-grained demographic inference by adding a new mutation model to msprime [71]. We simulated a sawtooth demographic model with cyclical population size changes over time and a baseline effective population size of 2×10^5 individuals. Simulations were conducted on a 5Mbp sequence with a recombination rate of

3.4×10^{-8} per base pair per generation (ploidy=1), to isolate the influence of methylation dynamics.

A custom matrix mutation simulation was implemented to model methylation and demethylation processes, employing 2 allelic states: 0 (unmethylated) and 1 (methylated). The model incorporates 3 key rates: the site introduction rate (μ), methylation rate (β), and demethylation rate (δ). The methylation and demethylation rates are measured as factors of the site entry rate, where β = methylation factor·μ and δ = demethylation factor·μ. Transition probabilities between the unmethylated and methylated states are determined by the ratio $\beta/(\beta+\delta)$ for methylation and $\delta/(\beta+\delta)$ for demethylation. The resulting 2×2 transition matrix encapsulates these probabilities:

$$\begin{bmatrix} 1 - [\beta/(\beta+\delta)] & \beta/(\beta+\delta) \\ \delta/(\beta+\delta) & 1 - [\delta/(\beta+\delta)] \end{bmatrix}$$

This framework allowed us to explore various methylation scenarios by adjusting β and δ relative to μ, while keeping r constant. We investigated cases where $\beta = \mu$ and $\delta = 2.5\mu$, $\beta = 10\mu$ and $\delta = 25\mu$, and $\beta = 100\mu$ and $\delta = 250\mu$, representing low, medium, and high methylation dynamics respectively, with the demethylation rate 2.5 times higher than the methylation rate. This approach enabled the examination of the range of inference when scaling the number of markers per window (here window size 1,000) does not match the respective average coalescent times, because they are no longer directly proportional.

Declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

The scripts for analyzing and plotting all results, except for the demographic inference, have been published on GitHub (arunkumarramesh/methevolve) and archived using Zenodo (https://doi.org/10.5281/zenodo.13748801). The demographic inference method is available on GitHub (kevinkorfmann/aTMi) and has been archived using Zenodo (https://doi.org/10.5281/zenodo.13332833).

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

RA and AT designed the research. RA, KK, AW, BH, CG, and YW performed the research. RA, AT, KK, and AW wrote the paper. All authors read and approved the final manuscript.

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