Characterizing cytosine methylation of polymorphic human transposable element insertions using human pangenome resources

Xiaoyu Zhuo[1,2], Chad Tomlinson[3], Edward A. Belter, Jr[3], Prashant Kumar Kuntala[1,2], Wesley N. Saintilnord[1,2], Tina Lindsay[1,3], Juan Macias[1,2], Human Pangenome Reference Consortium, Robert S. Fulton[1,3], Ting Wang[1,2,3]

[1]Department of Genetics, Washington University School of Medicine, St. Louis, MO, USA

[2]The Edison Family Center for Genome Sciences and Systems Biology, Washington University School of Medicine, St. Louis, MO, USA

[3]McDonnell Genome Institute, Washington University School of Medicine, St. Louis, MO, USA

Abstract

Cytosine methylation is an important epigenetic modification that plays a crucial role in

genomic regulation. The conventional second generation sequencing based bisulfite

conversion methods used to interrogate cytosine methylation require comparing

bisulfited-treated reads with a reference genome for methylation calling. Therefore, it

cannot characterize the methylation of unaligned regions. Taking advantage of the recent

improvement of the third generation sequencing, we investigated the methylation pattern

of human lymphoblastoid cell lines (LCLs) of non-reference insertions from the human

population, with a focus on polymorphic transposable elements. We first characterized

whole-genome CpG methylation using both SMRT and nanopore technology and

benchmarked their performance against WGBS using five human LCLs included in the draft

Human Pangenome Reference. Both methods are highly correlated with the conventional

WGBS results across the genome. The level of differences between PacBio and ONT on the

same sample is comparable with that of two replicates of WGBS of the same sample. Using

long-read data from the draft Human Pangenome Reference, we characterized CpG

methylation of non-reference insertions, especially polymorphic transposable elements.

We focused on addressing two questions: 1) do newly inserted TEs adopt the methylation

pattern of their genomic context? and 2) do methylation spread from new TE insertions to

their flanking regions? We found that most non-TE insertions exhibit DNA methylation

pattern consistent with their genomic context, but TE insertions are consistently

methylated, with a few exceptions. We also found limited methylation spreading from

Alu/L1 insertions to their flanking genomic regions. We investigated INDEL frequency in

both hypermethylated and hypomethylated CpG islands and found INDELs are enriched in

hypermethylated CpG islands. Our work demonstrated the methylation calling capability of

the 3rd generation sequencing and its unique advantage in characterizing epigenomic

features within non-reference positions.

Introduction

Cytosine methylation at CpG sites is prevalent in vertebrate genomes and the majority of

CpG sites in the human genome are methylated in most somatic tissues[1–3]. It is generally

believed that the CpG methylation is a repressive mark commonly associated with

heterochromatin and transposable elements (TEs), but is absent from promoter of active

genes[4]. In addition, methylation pattern is dynamic during development and disease

progression[5,6]. During evolution, methylation-mediated deamination converts methylated

cytosine to thymine, causing the general depletion of CpG sites in most vertebrate genomes.

The remaining regions enriched with CG motif compared with the genome background are

called CpG islands (CGIs), and they represent regions which remain unmethylated in germ

cells during evolution. Many CGIs are found in the promoters of conserved genes[7,8].

Cytosine methylation also responds to new genetic element insertions. For example, newly

inserted TEs are hypermethylated and the methylation mark can spread from the insertion

site to the flanking regions until blocked by other regulators[9,10], resembling the spreading

of heterochromatin[11]. The spreading of TE DNA methylation can affect the host genome

during evolution[12].

Given the importance of CpG methylation in genome regulation and evolution, considerable

efforts have been devoted to characterizing cytosine methylation. Microarray based

methylation chip, MeDIP-seq, MRE-seq, and RRBS-seq are all popular options to interrogate

methylation states of different CpGs across the genome[13-16]. Among these technologies,

Whole Genome Bisulfite Sequencing (WGBS) has been considered the gold standard in

cytosine methylation calling since its debut in the 2nd generation sequencing era[17-19].

Despite its many advantages, WGBS has several limitations. For example, the bisulfite

treatment that chemically distinguishes methylated from unmethylated cytosine damages

the DNA molecules and complicates the library preparation before sequencing. In addition,

WGBS typically relies on identifying mismatches between bisulfite-treated reads and the

reference genome to call methylation, making methylation calling of cytosines of non-

reference regions non-trivial. There are new methods developed recently to improve WGBS

but ultimately, they are limited by the 2nd generation sequencing[20,21].

The 3rd generation sequencing technologies have greatly matured in recent years[22,23]. This

improvement results in reads that are much longer, and the ability to distinguish

methylated cytosines and possibly other modified bases from unmodified ones during

basecalling[24,25]. Thus, methylation calling and sequencing can be done simultaneously,

making cytosine methylation calling much simpler and more accessible without resort to

specific chemical treatment to target cytosine methylation. Despite the promising outlook,

the signal changes caused by methylation is usually small and variable, and it is not until

the recent development of deep learning models that CpG methylation calling on SMRT and

Nanopore data has seen dramatic improvement in accuracy[26-28]. Recently, the third

generation sequencing were used to characterize the high resolution methylation profile of

repetitive elements[29,30].

Taking advantage of the high coverage of the Human Pangenome Reference Consortium

(HPRC) 3rd generation sequencing data and latest methylation calling methods, we

compared the whole-genome CpG methylation in five human lymphoblastoid cell lines

(LCLs) using Single Molecule, Real-Time (PacBio), Nanopore (ONT), and WGBS

technologies. After benchmarking the accuracies of methylation calling of the 3rd

generation sequencing, we investigated DNA methylation profiles of polymorphic TE

insertions, the relationship between DNA methylation patterns of the insertions and their

flanking genomic regions, as well as how could local methylation be affected by the new

insertions. Our results suggest that the 3rd generation sequencing is capable of accurately

characterizing CpG methylation at non-reference positions that are inaccessible with

conventional WGBS. Additionally, we revealed minimal methylation interaction between

TE insertions and their genomic context.

Results

Both PacBio HiFi and Nanopore ONT reads provide accurate DNA methylation estimation

The Human Pangenome Reference Consortium (HPRC) published the first human

pangenome reference graph representing 47 genetically diverse individuals[31]. In addition

to rich genetic information and various annotations, it also enabled direct methylation

analysis using long read raw sequencing data. Taking advantage of these resources, we

obtained HiFi methylation data of 32 samples (download) and performed additional CpG

methylation calling of ONT reads (R9.4.1) of five individuals who were part of the first draft

of the Human Pangenome Reference (HG00741, HG00621, HG01952, HG01978, and

HG03516) (Methods). In addition, we performed Whole Genome Bisulfite Sequencing

(WGBS) for these same five individuals (Methods). After calling CpG methylation, we

aligned all reads to the human reference genome hg38. Since the methylation calling of

both PacBio and ONT reads were obtained from raw reads directly without inferring from

reference sequences, we retained the per-molecule methylation estimation of both

reference positions and non-reference insertions. (Fig. 1a).

We first compared DNA methylation calls between HiFi, ONT, and WGBS for all CpG sites in

the reference genome hg38. We adopted a simple "pileup" method for calling methylation

level, which is a maximal likelihood estimate based on how many times a specific CpG is

called methylated or unmethylated among reads aligned to it (Methods). We also included

the deep learning based mathematical model (PB-model) developed by PacBio to estimate

methylation percentage of individual CpG sites in a given sample

(https://github.com/PacificBiosciences/pb-CpG-tools). We calculated mean average error

(MAE), 20% concordance, and Pearson correlation between WGBS, HiFi (pileup and PB-

model), and ONT for each sample in pairwise comparisons (HG00741 comparison in Fig. 1c

and the other four in Extended Data Fig. 1). We found ONT methylation calls highly

correlated with their matching WGBS result in all five samples (Fig. 1c and Extended Data

Fig. 1). Methylation percentages calculated by piling up HiFi reads did not match WGBS

results as well as ONT methylation calling (Fig. 1c). Upon close examination of the density

plot, we noticed a skewed methylation percentage distribution from HiFi pileup, with the

peaks of the methylation percentages located at ~20% and ~80% instead of 0% and 100%.

This observation suggests relatively low methylation calling accuracy per HiFi read (for

example, 20% accuracy a CpG site with 0% methylation will be presented as 20%

methylated). However, the PB-model resulted in a much better correlation/concordance

between the HiFi methylation percentage estimation and the WGBS (MAE: 0.1062; 20%

concordance: 0.846; Pearson correlation: 0.901). We examined the distribution of

methylation level across different genomic contexts (defined by the GM12878 chromHMM

states) and found strong concordance among WGBS, HiFi PB-model and ONT across all five

samples[32]. The HiFi pileup shared a similar trend but skewed toward intermediate

methylation levels (Fig. 1d). We then used the WashU Epigenome browser to illustrate the

comparisons between WGBS, HiFi pileup, HiFi PB-model and ONT (Fig. 1b). HiFi PB-model

clearly outperformed HiFi pileup and was chosen in all following analysis.

To gain a global view of the difference and similarity across methods, we performed

Principal Component Analysis (PCA) and plotted the first two Principal components in a 2D

plot for visualization (Fig. 1e). In all five samples, the two matching WGBS replicates

consistently clustered together; HiFi (PB-model) and ONT methylation results from the

same samples also clustered together. The PCA distance between WGBS and the long read

methylation results seemed to be larger than the distances between HiFi and ONT.

To better understand the scale of differences between the different methods, we defined

differentially methylated regions (DMRs) between HiFi (PB-model), ONT, and WGBS, as

well as between two WGBS replicates of the same sample[33]. Since the DMRs here were

defined using the same samples, they represented the false positive discoveries, and

allowed us to estimate an empirical false discovery rate. Using different thresholds, we

found that the numbers of falsely discovered DMRs between HiFi and ONT were

comparable with the numbers derived from the two WGBS replicates (Fig. 1f). Thus, the

methylation calling differences between HiFi and ONT was quite small, generally

comparable with the differences we observed between the two WGBS replicates.

Figure 1. a: Study design of methylation calling benchmarking. We performed CpG
methylation calling for five HPRC samples (HG00621, HG00741, HG01952, HG01978, and

HG03516), using PacBio, ONT, and WGBS. We mapped all reads to the human reference
genome hg38 to compare their difference. b: WashU Epigenome Browser screenshot of the
two WGBS replicates, HiFi pileup, HiFi PB-model, and ONT methylation of HG00741 on the
10 kb window around the TP53 gene promoter. All methylC tracks Y-axis percentage is
from 0% to 100%. c: whole genome methylation percentage correlation between WGBS,
HiFi pileup, HiFi PB-model, and ONT methylation. The whole genome methylation
percentage distribution is represented as a density plot. The correlation heatmap and
metrics (Mean Average Error, 20% concordance, and Pearson correlation) are plotted on
the left-bottom and right-top, respectively. d: Methylation percentage distribution of the
GM12878 15 chromHMM states across all five samples. The 15 chromHMM states are listed
on the X-axis and methylation calling results from different methods colored differently. e:
PCA plot of the top 2 principal components of the whole genome methylation from the five
HPRC samples. For each sample, we performed two replicates of WGBS in addition to HiFi
(PB-model) and ONT methylation calling. We use different shapes to represent different
methods (circle, triangle, and cross for ONT, HiFi, and WGBS) and different colors to
represent different samples (red, yellow, green, blue, and purple for HG00621, HG00741,
HG01952, HG01978, and HG03516, respectively). f: Number of falsely discovered
differentially methylated regions (DMRs) using different threshold cut-offs. Four different
thresholds (20% average methylation difference with at least 5 CpG sites, 20% average
methylation difference with at least 10 CpG sites, 30% average methylation difference with
at least 5 CpG sites, and 30% average methylation difference with at least 10 CpG sites) are
represented on the X-axis. The number of DMRs are represented on the Y-axis. The number
of DMRs between different methods under different conditions are plotted using different
colors.

The methylation patterns of TE insertions and their correlation with flanking regions

Because the 3rd generation methylation calling was conducted on raw reads without

aligning to the reference genome, it enabled methylation calling of non-reference regions

previously inaccessible with 2nd generation sequencing based methods, at least not

trivially. Thus, we investigated the methylation status of non-reference insertions with a

focus on polymorphic TE insertions, and their correlation with the methylation levels of

their flanking regions. Here we took advantage of the recent release of the draft Human

Pangenome Reference made available by the HPRC, which included HiFi reads of the 32

HPRC Year1 samples (download) as well as their variant calling results (download)[31]. We

further annotated insertions using the Transposable Element Insertion Annotation pipeline

xTEA[34]. We classified TE insertions into four categories: *Alu*, LINE1, SVA, and ERV. Non-

reference insertions other than TEs were classified as non-TE.

To help analyze and visualize non-reference insertions, we assembled chromosome level

individual diploid genome assemblies of the five HPRC individuals using hifiasm assemblies

(download) and mapped phased long reads onto maternal or paternal genomes. We also

developed methods to extract insertion sequences along with their methylation annotation

from BAM files mapped to either reference or individual genome (Fig. 2a, Methods). Using

these pipelines, we extracted and aligned TE insertions with methylation to their respected

TE consensus.

Figure 2. a: Schematic representation of our pipeline to extract non-reference insertions along with their methylation annotation. b: Per CpG HiFi methylation percentage of all non-reference *Alu* insertions. Each insertion is represented by a grey line and we used the average methylation of an insertion as Y-axis. We used the Blue-Red color scale to represent methylation status of each CpG sites (Blue: hypomethylated; Red: hypermethylated). A dotted line represents the cut-off (0.5) we used to filter lowest methylated regions to plot in c. c: Per CpG site methylation percentage of non-reference *Alu* insertions with average methylation < 0.5. Long-read methylation is colored with same color scale as Fig. 2b along *Alu* consensus (X-axis) with ONT methylation above and HiFi

methylation below the grey line representing insertions. All insertions were grouped by the
insertion position on hg38. d: The WashU Comparative Epigenome Browser screenshot of
the methylation status of *Alu* insertion at hg38:chr1:162791517-162791519 in different
samples. Methylation percentage derived from HiFi and ONT reads were plotted from 0-
100% scale below gene and RepeatMasker annotation. A genome-align track separated
haplotypes with and without insertion. It inserted at the boundary between a
hypomethylated region (promoter of HSD17B7) and a hypermethylated region (gene body
of HSD17B7).

We displayed the methylation of all CpG sites across different TEs in Fig. 2 and Extended

Data Fig. 2. In Fig. 2b we showed the HiFi methylation of each CpG site of all *Alu* insertions

vertically separated by their average methylation, and 97% of *Alu* insertions were

hypermethylated (defined as average methylation > 0.7) (Fig. 2b). In Fig. 2c we plotted

both ONT and HiFi methylation of *Alu* insertions with average methylation < 0.5 in the five

phased samples grouped by the insertion site. Out of 13 *Alu* insertions presented in at least

two haplotypes, the methylation status of 11 of them were shared across different

individuals (Fig. 2c). Both exceptions (chr1:162791517-162791519 and chr3:57998586-

57998588) were inserted at the boundaries of methylation valleys. For example, the *Alu*

insertion at chr1:162791517-162791519 was hypomethylated in the HG01952 paternal

haplotype but hypermethylated in all other alleles (Fig. 2c). We then built a datahub using

the WashU Comparative Epigenome Browser[35] and its associated methylC and modbed

tracks[36,37] (datahub). Instead of mapping sequencing reads from different samples to a

single reference genome, we aligned them to their respected individual assemblies and

anchored them on hg38 by using genome-align tracks. This allowed us to directly visualize

and compare the insertions between the genome assemblies, aligned long reads, as well as

their DNA methylation pattern. This *Alu* element was present within the first intron of the

HSD17B7 gene at the boundary between the hypomethylated promoter and the

hypermethylated gene body (Fig. 2d). Its hypomethylation in the HG01952 paternal

haplotype reflects a haplotype-specific boundary shift. This example highlights the

variation in regional dependance of methylation of specific *Alu* elements. The methylation

pattern of LTR5, SVA, and L1 insertions were similar to *Alu* in general and were shown in

Extended Data Fig. 2. Interestingly, for L1Hs and SVAs, we found several consistently

hypomethylated CpG sites surrounded by hypermethylated CpG sites (position 5875 in

L1Hs consensus, 1116 in SVA consensus, etc.) (Extended Data Fig. 2).

After characterizing the methylation patterns of TE insertions, we next evaluated the

relationship in DNA methylation levels between insertions and their flanking regions. We

calculated the average methylation levels of non-reference insertions and compared them

with the average methylation levels of their 300bp flanking regions on both directions (Fig.

3a). We plotted this relationship in Fig. 3b. Consistent with our observation in Fig. 2 and

Extended Data Fig. 2, it is evident that TE insertions, especially *Alu* and SVA insertions,

were highly methylated in general, regardless of the methylation levels of their flanking

regions. On average, we observed weak correlations of methylation between TEs and their

flanking regions (linear regression slope ~ 0.2, $R^2 \sim 0.1$), albeit being statistically significant

except for LTR (p value <2.2e-16, <2.2e-16, 0.27, 5e-4 of L1, *Alu*, LTR, and SVA,

respectively). This pattern is sharply distinct from non-TE insertions, whose methylation

levels were highly correlated with their nearby flanking regions (slope = 0.87, R^2 = 0.59)

(Fig. 3b).

Figure 3. a: Schematic representation of average methylation calculation of all insertions and associated 300bp flanking regions. b: Methylation correlation between insertions and 300bp flanking regions. The average methylation of insertions is represented on the Y-axis, while the methylation of flanking regions on the X-axis. *Alu*, LTR, LINE1, SVA, and non-TE insertions are represented by red, green, blue, and purple dots, respectively whereas non-TE insertions are labeled grey, serving as a background. Linear regression lines with standard errors are also plotted and labeled with same color scheme. c: Schematic representation of average methylation calculation of insertions within CpG islands and associated 300bp flanking regions. d: Methylation correlation between insertions within CpG islands and 300bp flanking regions. The average methylation of insertions is represented on the Y-axis, while the methylation of flanking regions on the X-axis. *Alu*, LTR, LINE1, SVA, and non-TE insertions are represented in the same way as they are in 3b. e: WashU Epigenome browser shots of a hypermethylated *Alu* insertion present in HG00621 but absent in HG03516 as characterized by WGBS, HiFi, and ONT methylation. Long-reads are separated by their haploid type. All the methylC tracks display methylation percentage from 0%-100%. f: Depiction of a hypomethylated *Alu* insertion within CpG island present in HG03516 paternal but absent in HG03516 maternal. Both HiFi and ONT reads are separated by their haploid type and aligned to the respective haploid assembly. A genome-align track was used to illustrate the heterozygous insertion. g: Schematic representation of insertion-flanking methylation regression as the function of insertion-flanking distance. For each distance from 100bp to 10kb, we performed linear regression between insertion and flanking average methylation and estimated the linear regression slope and standard errors. h: Linear regression slope between insertion and flanking methylation as the function of the insertion-flanking distance from 10kb upstream to 10kb downstream. *Alu*, LTR, LINE1, SVA and non-TE insertions are plotted in separated plots with different colors. Standard Error for each window were shown as black bar. i: Linear regression slope between non-TE insertion and flanking methylation similar to 3h. All non-TE insertions were separated by their length and plotted by the following five bins: 30bp-100bp, 100bp-300bp, 300bp-1kb, 1kb-3kb.

CpG island (CGI) is an important genomic feature, and their methylation status is highly

relevant to gene regulation[1]. When we restricted the above analysis to non-TE insertions

within CGIs only (Fig. 3c), we found the insertion-flanking methylation correlation to be

stronger (slope = 0.97, R^2 = 0.89) (Fig. 3d). Surprisingly, this strong correlation was also

extended to TE insertions within CGIs (colored dots and regression line Fig. 3d). For

example, genome-wide *Alu* insertions are generally hypermethylated with no apparent

relationship with that of their flanking regions (Fig. 3b). However, *Alu* methylation states

are correlated with their flanking methylation when only insertions within CGIs are

selected (slope = 0.89, R^2 = 0.6) (Fig. 3d). Thus, methylation of TE insertions seems to

follow different rules between CGIs and other parts of the genome.

We displayed two examples using the WashU comparative Epigenome Browser. we found a

polymorphic *Alu* insertion at hg38:chr1:8386566 that was absent in HG03516 and present

in HG00621 (Fig. 3e). Since this insertion was homozygous in HG00621, we also displayed

the WGBS short reads mapped to the maternal assembly. Since the insertion was

homozygous, mapping the same WGBS reads to either paternal or maternal assembly did

not make a difference (Extended Data Fig. 3a). The *Alu* insertion in HG00621was

hypermethylated (methylation level = 95.3%, 95.8% and 96.2% based on HiFi, ONT and

WGBS, respectively), as illustrated by both the individual aligned HiFi reads and the

methylation percentage tracks. There were only two CpG sites within the 500bp flanking

window and they were intermediately methylated (average methylation level = 63.4%

combining all three methods) (Fig. 3e).

At hg38:chr11:59565869 the HG03516 maternal and the paternal genome were different

by an *Alu* insertion in the paternal genome, as illustrated by the genome-align track. The

Alu insertion was in an hypomethylated CpG island (chr11:59565807-59566091, with

average maternal CGI methylation = 3.9%, paternal CGI methylation = 7.9%) and was itself

hypomethylated (*Alu* methylation = 10.3%, 8.7%, and 4.0% based on HiFi, ONT and WGBS,

respectively) (Fig. 3f and Extended Data Fig. 3b).

Our analysis thus far has revealed a strong correlation in DNA methylation levels between

non-TE insertions and their 300bp flanking regions, and a much weaker correlation when

the insertions are TEs. We next investigated the insertion-flanking methylation correlation

beyond 300 bp as a function of the distance between the insertion and the nearby regions.

For each non-reference insertion, we calculated DNA methylation levels in its 10 kb

flanking regions on both directions at a resolution of 100-bp non-overlapping windows

(Fig. 3g). We grouped the average methylation of all 100-bp windows from different

insertions by their distance from the insertion sites and performed linear regression

between insertion and flanking regions. Since the slopes of the linear regression can reflect

the methylation correlation between these regions, we then displayed the slope of the

linear regression as a function of the distance between the flanking windows and the

insertion (Fig. 3h). This analysis revealed that the methylation correlation slope between

non-TE insertions and their flanking windows quickly faded away as the distance between

the flanking window and insertion site increased, with an estimated elbow point being

~2.5kb away from the insertion. The slope decayed to and stayed at around 0.1 when the

distance reached 5kb and beyond. TEs once again displayed a strikingly distinct pattern.

There was no observable correlation between LINE1, SVA, and LTR insertions and their

flanking regions. We did however observe a weak correlation between *Alu* insertions and

their flanking regions but it also quickly faded away (Fig. 3h). This observation could be

confounded by the fact that TE insertions are longer than non-TE insertions (length

distribution of TE insertions in Extended Data Fig. 3c). To rule out this possibility, we

investigated how the size of non-TE insertion could affect the insertion-flanking

methylation correlation. If the methylation correlation is merely a function of the insertion

size, we would expect ~300bp and ~1000bp non-TE insertions behave similarly to *Alu* and

LTR insertions, for example. We categorized non-TE insertions by their sizes into five bins,

then calculated the regression slope in each bin (Fig. 3i). Despite a slightly decrease of the

peak methylation correlation as a function of increased non-TE insertion size, the

correlation was much higher than that of TE insertions of comparable length (for example,

the slope distribution of 300-1000bp non-TE insertions was much higher than that of *Alu*

and LTR insertions). This suggests that the methylation of non-TE insertions, but not TE

insertions, are highly correlated with that of their flanking regions.

Limited methylation spreading from polymorphic human L1s/*Alus* to flanking regions

Previous studies have suggested that repressive chromatin marks including DNA

methylation deposited on newly inserted TEs can spread beyond TE/genome

boundary[10,11,38]. This relationship has not been examined for human polymorphic TEs at a

genome-wide scale, or for other types of human polymorphic insertions. Some non-

reference insertions could be deletion events in the human population[39]. However, TE

insertions are essentially homoplasy-free[40] and represent recent insertions that are

polymorphic in the human population. Thus, we explored how these insertions might have

interacted with their genomic insertion sites epigenetically, either influencing DNA

methylation of the insertion sites, or being influenced by the DNA methylation pattern of

the insertion sites. We also characterized the methylation pattern of other non-reference

insertions as a comparison.

For each polymorphic non-reference insertion relative to hg38, we phased HiFi reads from

all 32 HPRC Year1 samples and separated them into two groups: alleles with the insertion

and alleles without the insertion (Fig. 4a). We calculated the average methylation level of

the inserted regions (insertion), the 300bp flanking regions of the insertion from both ends

(insertion flanking), as well as the same flanking regions of the allele without insertion

(empty flanking) (Fig. 4a).

Figure 4. a: Schematic representation of a polymorphic insertion with aligned long reads. The allele without the insertion site (top) and the allele with the insertion site (bottom) are represented as reference allele and insertion allele. The average methylation level of the insertion, insertion flanking regions, and empty flanking regions are calculated from reads from all 32 samples. We then calculated flanking methylation difference by subtracting the methylation level of empty flanking from that of insertion flanking. b: methylation level of empty flanking (X-axis), insertion flanking (Y-axis), and non-TE inserted regions (color scale). c: Similar to Fig. 4b, but the methylation level of different TE insertions are presented and separated by the TE insertion types. d: dot plot representing the relationship between methylation level of insertion (Y-axis) with that of the flanking region (X-axis). Methylation percentage of insertions with flanking differences within 25% are boxed and labeled. e: TE insertion flanking methylation differences plotted the sample way as in Fig. 4d. Different TE insertions are distinguished by different colors. Percentage of all insertions within 25% differences and the average flanking methylation differences of different TEs are labeled.

To illustrate the relationship between these three regions, we also plotted the methylation level of insertion flanking and empty flanking on the X-Y axis using a dot plot and colored the dot using the methylation level of insertions (Fig. 4b, c). In general, the methylation level of insertion, insertion flanking and empty flanking correlated with each other in case of non-TE insertions (Fig. 4b). As for TE insertions, the flanking methylation level of insertion and empty site showed a strong correlation despite the high methylation of the insertion (Fig. 4c).

To better characterize the subtle changes in flanking methylation level between insertion and empty sites, we defined the flanking methylation difference of each insertion by subtracting the flanking methylation of empty site from the flanking methylation of insertion sites (Fig. 4a). We reasoned that an allele without a TE insertion represents the ancestral allele[40]. If the insertion increases flanking methylation, the difference would be positive; and if it decreases methylation the difference would be negative. On the other

hand, if the insertion has no impact on flanking region methylation, the difference would be

zero.

We first plotted the relationship between the flanking methylation differences and the

methylation of non-TE insertions (Fig. 4d). The overall methylation differences between

orthologous flanking regions with or without insertions were heavily distributed around

zero, (99% (41755/42168) of the data points being within the -25% to +25% range), and

independent of the methylation level of the insertion itself. However, we observed a few

cases in which hypermethylated insertions were associated with increased flanking

methylation while hypomethylated insertions were associated with decreased methylation

(Fig. 4d). Altogether, these results strongly suggest that, albeit a few individual exceptions,

non-TE insertions generally do not affect flanking region methylation.

We then investigated the same relationship in the context of TE insertions (Fig. 4e).

Comparing with non-TE insertions, the range of the methylation differences was slightly

broader (96%, 5218/5413, within -25% and 25%), indicating increased variations in

flanking region methylation associated with TE insertions (F-Test to Compare Two

Variances: F=2.4528, df1=5412, df2=42167, p-value < 2.2e-16). On average, the flanking

methylation centered around zero for LTR and SVA insertions. However, *Alu* and L1

insertions were more highly associated with increased flanking methylation (117 and 3

increased by 25%, 66 and 1 decreased by 25%, respectively). On average, flanking

methylation increased by 3.2% (p < 2e-16) and 4.0% (p = 5e-14) for *Alu* and L1 insertions,

respectively. The range of methylation differences we observed was quite large. For

example, the mean methylation level of inserted *Alus* was 82.7%, and *Alu* insertions with

methylation level greater than this mean value were associated with a flanking region

methylation difference ranging from -42.74% to +42.66%, with 21 of them associated with

an increased flanking region methylation by greater than 30%. Similarly, the mean

methylation level of inserted L1s was 69.2%, and L1 insertions with methylation level

greater than this mean value were associated with a flanking region methylation difference

ranging from -30.1% to +27.8%, with none of them associated with an increased flanking

region methylation by greater than 30%. These examples are not fully consistent with the

hypothesis that DNA methylation deposited on newly inserted TEs could spread and

increase local DNA methylation level. Based on our genome-wide assessment, the

spreading is limited, and more drastic influence of TEs on nearby genomic methylation may

be an exception rather than the rule.

To further investigate the magnitude and the distance to which DNA methylation spreads

from polymorphic TE insertions, we aggregated all polymorphic insertions and plotted the

average methylation trendline based on their relative position in relation to the insertion

sites from the reference genome (Fig. 5a). We found a subtle increase of methylation

flanking the polymorphic L1/*Alu* insertions, with the highest increase right at the insertion

site (3.1% for L1 and 3.2% for *Alu*). This flanking methylation difference between insertion

and empty site decreased as the distance to insertion position increased, and the

methylation difference diminished at ~1kb away from the insertion site (Fig. 5a). The exact

same pattern is recapitulated by both the ONT methylation data and the WGBS data from

the five HPRC individuals (Fig. 5b, c), where we phased ONT reads and mapped the WGBS

reads of homozygous insertions to the individual's own genome assemblies (Methods) (Fig.

5c). Taken together, these data suggest polymorphic *Alu* and L1 insertions are associated

with slightly elevated DNA methylation levels at their insertion sites, and the effect is

localized within a thousand base pairs.

Figure 5. a: Average flanking methylation percentage trendline predicted by HiFi reads of either empty or TE insertion site in the reference genome. Average methylation derived from both empty and insertion alleles are represented by different color (blue represents insertion flanking while red represents empty flanking). Different TE types are separated by the grid. b: Average flanking methylation percentage trendline predicted by ONT reads of either empty or TE insertion site in the reference genome similar to Fig. 5a. c: Average flanking methylation percentage trendline predicted by WGBS of homozygous *Alu* insertions and empty sites in the reference genome similar to Fig. 5a. d: WashU Epigenome Browser shots of a hypermethylated *Alu* insertion within a hypomethylated valley present in HG00621 but absent in HG00741 characterized by WGBS, HiFi, and ONT methylation. Long-reads were separated by their haploid type, all the methylC tracks displaying methylation percentage from 0%-100%. e: Zoom-in view of the methylation of the same *Alu* element from Fig. 5d. The 3 CpG sites within 200bp of the insertion site went from hypomethylated to hypermethylated associated with the *Alu* insertion.

Here we illustrated an example where an *Alu* insertion was associated with limited DNA methylation spreading in its flanking regions (Fig. 5d, e). In Fig. 5d, we displayed a homozygous *Alu* insertion present in HG00621 but absent in HG00741 (this polymorphic *Alu* insertion was also found in HG03516 but absent in HG01952 and HG01978). The insertion site was within a hypomethylation valley in HG00741 (hg38:chr1:40058800-40060800, methylation level 4%) where the *Alu* insertion was absent. In HG00621, the *Alu* insertion was hypermethylated (methylation level 85%), and methylation level of the hypomethylation valley was elevated to 21% (Fig. 5d). Specifically, there were three CpG sites 200bp upstream of the insertion that were lowly methylated in HG00741 (18%, 5%, 4%) but highly methylated in HG00621 (89%, 88%, 93%). On the other hand, multiple CpG sites more than 300bp downstream from the insertion site seemed to have remained their hypomethylated state (3 CpGs, 3% in HG00741, 5% in HG00621) (Fig. 5e).

Elevated insertion/deletion (INDEL) rate in hypermethylated CpG Islands

It is well known that the mutation rate is much higher at methylated CpG sites due to the deamination of methylated cytosine[7]. However, we know little about how methylation level would affect other mutation processes including insertions/deletions (INDELs). Previous work comparing human and chimpanzee reference genomes as well as 1000 Genome Project data revealed a surprising finding that CpG islands (CGIs) are enriched with indels with moderate sizes (20 bp - 50 bp)[42]. Using the Human Pangenome resource, we set to investigate whether DNA methylation of CGIs would affect their INDEL frequency. We first grouped CGIs as promoter CGI and non-promoter CGI based on whether they overlapped annotated promoters and compared their average methylation distribution (Fig. 6a). We found that promoter CGIs were overwhelmingly unmethylated while most of the non-promoter CGIs were highly methylated, consistent with previous findings[16,43] (Fig. 6a). Since intermediately methylated CGIs were rare, we divided all CGIs into hypermethylated and hypomethylated ones using the 50% average methylation as a cut-off (Fig. 6a). It is possible that many non-promoter CGIs represent unannotated transcription start sites in the genome[16]. To avoid CGI methylation status confounded by their relationship to annotated promoters (Fig. 6a), we kept promoter and non-promoter CGIs separated in the following analysis.

Figure 6. a: Histograms of the number of CpG islands with different average methylation percentage. The histogram represent number of CpG islands in promoter (left), number of CpG islands outside of any promoter (non-promoter, right). b: INDELs derived from HPRC samples length-frequency relationship from 1bp to 150bp. INDEL frequency in hypermethylated CpG islands, in hypomethylated CpG islands, and in two (shuffled hypermethylated regions as shuffle 1, shuffled hypomethylated regions as shuffle 2) matching genome-wide controls are represented by different colors (Red, green, blue, and

purple represents hypermethylated CGI, hypomethylated CGI, shuffle 1, and shuffle 2,
respectively). c: Violin plot representing INDEL frequency distribution from 20-50bp of the
same four categories of CpG islands as in Fig. 6b. Paired T-test p-values are labeled next to
the violin plot bars. d: INDELs derived from 1000 genome project length-frequency
relationship from 1bp to 150bp. INDEL frequency in hypermethylated CpG islands, in
hypomethylated CpG islands, and in two matching genome-wide controls are represented
by different colors. e: Violin plot representing INDEL frequency distribution from 20-50bp
of the same four categories of CpG islands as in Fig. 6d. T-test p-values are labeled next to
the violin plot bars. f: The same CpG island INDEL frequency vs methylation plotted as in
Fig. 6b and Fig. 6d but with INDELs identified by HGSVC. g: Violin plot representing INDEL
frequency distribution from 20-50bp of the same four categories of CpG islands as in Fig. 6f.
T-test p-values are labeled next to the violin plot bars.

To further evaluate the relationship between DNA methylation and INDEL frequency, we

plotted the relationship between INDEL size and their frequency within CGIs normalized by

the CGI length (Fig. 6b). We shuffled both hypermethylated and hypomethylated CGIs

within the genome used as background INDEL frequency, and calculated the INDEL

frequency the same way as background INDEL frequency. We observed a decrease of

INDEL frequency as a function of increase INDEL size across all comparisons, indicating a

negative correlation between INDEL size and frequency. In both promoter and non-

promoter CGIs, we recapitulated the result of enrichment of 20-50bp INDELs in CpG islands

compared to the shuffled genomic control (Fig. 6c, paired t-test p-value = 1.4×10^{-9} and

3.1×10^{-14} in promoter and non-promoter regions, respectively)[42]. We found

hypermethylated CpG islands had the highest INDEL frequency among these groups (Fig.

6c). The difference for INDELs > 10bp was quite staggering (Fig. 6b).

Using the same CGI and methylation annotation, we repeated the analysis using INDELs

derived from the 1000 genome project[44]. We found the enrichment of 20-50bp INDELs in

CpG islands compared to the shuffled genomic control (Fig. 6d, e, p-value = 9×10^{-7} and

2×10^{-5} in promoter and non-promoter regions, respectively)[42]. However, we did not find

any significant difference between hypermethylated and hypomethylated CpG islands

within either promoter or non-promoter CGIs (p-value = 0.43 and 0.30 in promoter and

non-promoter regions, respectively) (Fig. 6e). We suspect that the 2nd generation

sequencing, which the 1000 Genome Project relied upon, under characterized INDELs

greater than 10bp leading to the inability to discern the INDEL frequency difference

between hypomethylated and hypermethylated CGIs (Fig. 6d). To verify our findings

derived from HPRC long reads, we performed the same analysis but using the INDEL call

set derived from 3rd generation sequencing generated by the Human Genome Structural

Variation Consortium[45]. We confirmed the increased INDEL frequency in hypermethylated

CGIs from both promoter and non-promoter regions (Fig. 6f, g). Taken together, combining

variant calling and methylation calling using HiFi reads, we found that hypermethylated

CGIs had a higher frequency of INDELs greater than 10bp than both hypomethylated CGIs

and genomic background. Our observation here highlighted the advantage of 3rd

generation sequencing in INDEL calling in addition to methylation calling, and the need for

additional work to better understand the mechanism behind this phenomenon.

Discussion

Characterizing cytosine methylation is important for both evolutionary analysis and tissue-

specific gene regulation. However, conventional bisulfite or enzyme conversion-based

methods do not readily characterize methylation of repetitive regions or non-reference

regions. Using 3rd generation sequencing, we can call methylation during the base calling

step, greatly simplifying the methylation calling process and allowing new investigations

into the genomic methylation. Here we compared the methylation calling results between

HiFi, ONT, and WGBS from five HPRC LCL samples, and we found both HiFi and ONT can

measure CpG methylation in human with high correlation and concordance with WGBS.

How are genomic insertions, in particular transposable element insertions, methylated, and

how do they affect the methylation level of their flanking regions, has been a long-standing

question in the field. It has promoted several paradigms, especially in the context of

spreading of epigenetic modifications. For example, the hypermethylation of an inserted B2

element close to the Aprt promoter in mouse genome can spread to nearby CpG sites until

stopped by SP1 binding[10]. By examining CpG density flanking *Alu* insertions, Zhou et al. also

found evidence of CpG methylation spreading from old TEs to flanking regions during

evolution[12]. Recently, Lanciano et al. described examples of LINE1 insertion in cancer cell

lines affecting the methylation level of nearby regions up to 300bp upstream[46]. These

previous studies provided enormous insights on how newly inserted transposable

elements are epigenetically modified and how the modifications influence genomic

neighborhood. However, most represented specific examples or anecdotes, leaving the

question open as to what degree these examples represent the genome-scale rules or

exceptions.

Taking advantage of both SV and methylation calling using the HiFi reads from 32 samples

of HPRC Year1 dataset, we addressed this question by analyzing differential methylation

between alleles with polymorphic insertions at a genome-wide scale. Our analysis suggests

that the methylation of non-TE insertions is influenced by their genomic context.

Consistent with Lanciano et al., we did find limited methylation spreading from L1 to

nearby regions. However, the effect is very small (on average ~3% increase of methylation

within 300bp). The minimum spreading of methylation from polymorphic TE insertions to

their flanking regions we found suggests that methylation spreading is a slow evolutionary

process with limited effect after TE insertion but can potentially have large impact at

evolutionary timescale[12].

To visualize the methylation of non-reference insertions, we mapped reads to the high

quality individual assembly and displayed them on the WashU Epigenome Browser using

the genome comparison feature[35,47]. However, this approach is limited by the underlying

pairwise alignment and more crucially, the availability of high quality individual

assemblies. We hope the development of pangenome based tools would facilitate data

display of non-reference sequences in the future.

Using the HPRC long read methylation data, we also found hypermethylated CpG islands

enriched with INDELs, further clarifying the initial discovery from 2020[42]. We envision the

publicly available long read methylation data can be used to address other questions in the

biomedical field, and we invite other scientists to explore the rich, high-fidelity HPRC

dataset[31].

Methods

Genome assembly and scaffolding

The genome assemblies used in this study were produced for the draft human pangenome,

combining PacBio HiFi long-read and Illumina short-read sequencing for de novo assembly

with parental short-read data used to for phasing of these assemblies. Phased contig

assembly was performed using hifiasm[48]. Post-assembly, the RagTag toolset was employed

for reference-guided scaffolding, organizing contigs into structured, phased chromosomal

assemblies[49]. Validation was performed using BioNano optical mapping, in order to detect

and amend potential assembly inaccuracies[50]. For each of the 10 assemblies derived from

the five diploid samples, we created a whole-genome pairewise alignment BAM file with

hg38 using minimap2[51].

Whole Genome Bisulfite Sequencing (WGBS)

The cytosine methylation was estimated by mapping to reference genome hg38 or the

individual assemblies using the standard WGBS pipeline Bismark as described by Lee et

al[52,53]. WGBS QC data including bisulfite conversion rate and mapping ratios is available in

Supplementary Table 1.

PacBio HiFi Methylation

PacBio single-molecule high fidelity (HiFi) Circular Consensus Sequencing (CCS) reads with

kinetics tags can be generated using pbccs (https://github.com/nlhepler/pbccs). We then

predicted cytosine methylation probability per molecule in all CpG context by applying

primrose to PacBio HiFi reads (https://github.com/PacificBiosciences/jasmine). The CpG

methylation probability was saved as the ML and MM tags in the BAM file following

standard BAM format convention (http://samtools.github.io/hts-specs/SAMtags.pdf).

Unaligned HiFi BAM files were aligned to human reference genome hg38 using PacBio

pbmm2 (https://github.com/PacificBiosciences/pbmm2), and CpG methylation percentage

on the reference genome were calculated using PacBio pb-CpG-tools

(https://github.com/PacificBiosciences/pb-CpG-tools). We ran the methylation percentage

calculation twice for each alignment using both "count" and "model" as pileup (–pileup-

mode count and –pileup-mode model).

Nanopore ONT methylation

We downloaded raw sequencing signal of ONT Nanopore (FAST5 files) of the same five

samples and performed methylation calling using basecaller guppy with methylation model

remora (https://github.com/nanoporetech/remora). CpG methylation probability of ONT

reads were estimated using Nanopore basecaller Guppy v6 with remora methylation model

(v9.4.1) (https://community.nanoporetech.com). The CpG methylation probability were

saved as the standard ML and MM tags in the BAM format (http://samtools.github.io/hts-

specs/SAMtags.pdf). ONT unaligned BAM files were aligned to human reference genome

hg38 using minimap2 (https://github.com/lh3/minimap2), and methylation percentage

were calculated using modbam2bed (https://github.com/epi2me-labs/modbam2bed).

Methylation comparison

With genome-wide methylation percentage of all three methods calculated, we made

pairwise correlation heatmap, PCA plot and calculated the mean average error, 20%

concordance, and person correlation using R[54,55]. We also applied DSS to define pairwise

differential methylation regions (DMRs)[33,56].

Long reads phasing

We used HiPhase for HiFi reads phasing[57]. To determine in each phase block which

haplotype is paternal, and which is maternal, we downloaded HiFi reads used for

constructing paternal and maternal assemblies from hifiasm output gfa files (HG00621,

HG00741, HG01952, HG01978, HG03516). We labeled the haplotype paternal if the

number of reads labeled with it from the same phase block used for paternal assembly is

>10 times higher than that used for maternal assembly, otherwise maternal. Once we

separated HiFi reads to paternal and maternal with whatshap[58], we aligned them to the

individual paternal and maternal assemblies, accordingly using pbmm2

(https://github.com/PacificBiosciences/pbmm2). At last, we calculated the genome-wide

methylation percentage on individual assemblies using pb-CpG-tools

(https://github.com/PacificBiosciences/pb-CpG-tools).

To phase ONT reads according to the individual assemblies, we created a diploid VCF file

for each sample using dipcall (https://github.com/lh3/dipcall)[59] and haptagged all reads

using haplotype information from the VCF file. We then separated paternal and maternal

reads using whatshap[58] and aligned them to paternal and maternal assembly using

minimap2[60], respectively. At last, we converted the bam file to methylbed files with

modbam2bed (https://github.com/epi2me-labs/modbam2bed).

Individual genome datahub

For each pairwise genome alignment between hg38 and individual genome, we created a

genome-align track file using the pairwise genome alignment BAM file[35]. We built

individual genome assembly of both maternal and paternal chromosomes of the five

samples (10 assemblies in total) and aligned each of them to the hg38 to create genome-

align tracks. We also phased HiFi reads using HiPhase using alignment to hg38 and

assigned haplotypes to paternal/maternal for each phasing block based on hifiasm

assembly construction graph[48,57]. We then aligned maternal and paternal HiFi reads to the

maternal/paternal assembly separately for each of the five samples. Applying the genome-

align track we anchored gene, repeat, and CpG island annotations from hg38 onto the

individual genomes. We colored each CpG site by their methylation prediction (red:

methylated; blue: unmethylated) per HiFi read using the modbed tracks and displayed

piled up methylation level using the methylC track. Both modbed and methylC tracks were

mapped to the individual genome. Combining genome-align, methylC, and modbed track

files, we created three datahubs on the WashU Epigenome browser representing HiFi, ONT,

and WGBS data

(https://epigenomegateway.wustl.edu/browser/?genome=hg38&hub=https://wangcluste

r.wustl.edu/~xzhuo/hifi_methylation/hifi.all.json,

https://epigenomegateway.wustl.edu/browser/?genome=hg38&hub=https://wangcluster

.wustl.edu/~xzhuo/hifi_methylation/ont.all.json,

<https://wangcluster.wustl.edu/~xzhuo/hifi_methylation/wgbs_individual/wgbs.all.json)[3

6,37,47].

At last, we created a browser session for each panel in screenshot (Fig. 2d:

https://epigenomegateway.wustl.edu/browser/?sessionFile=https://wangcluster.wustl.ed

u/~xzhuo/hifi_methylation/Fig2D.session.json; Fig. 3e:

https://epigenomegateway.wustl.edu/browser/?sessionFile=https://wangcluster.wustl.ed

u/~xzhuo/hifi_methylation/Fig3E.session.json; Fig3. f:

https://epigenomegateway.wustl.edu/browser/?sessionFile=https://wangcluster.wustl.ed

u/~xzhuo/hifi_methylation/Fig3F.session.json; Fig. 5d-e:

https://epigenomegateway.wustl.edu/browser/?sessionFile=https://wangcluster.wustl.ed

u/~xzhuo/hifi_methylation/Alu.spread.session.json).

671 **Structural variation and TE annotation**

672 We obtained the structural variations of each sample from HPRC consortium (Download[31].

673 To further annotate transposable element insertions among all structural variations, we

674 ran xTEA on the same PacBio HiFi library mapped to hg38[34]. We then intersected the

675 coordinates of TE insertions with SV and annotated which SVs are TE insertions (Supp.

676 Table 2).

677 With TE insertions annotated in all samples, we developed two methods to calculate

678 methylation percentage per CpG site of all TE insertions. With individual assembly

679 available, we extracted TE sequences and their methylation percentage based on the

680 insertion coordinates after aligning long-reads with methylation to the individual genomes

681 and calculating methylation percentage using pb-CpG-tools or modkit pileup. We then

682 constructed a new unmapped BAM file of inserted TE copies and attached methylation

683 percentage using modified base tags (MM and ML) (bam.creation.py). At last, we mapped

684 the new BAM file to TE consensus using Minimap2 to align CpG methylation percentage to

685 the TE consensus.

686 We also made another script for samples mapped to reference genome. Using a BED file of

687 annotated insertion sites, it can extract inserted and soft-clipped sequences from raw reads

688 and generate a new unmapped BAM file of inserted sequences with base modification tags

689 (MM and ML) (bam.extractInsertion.py). We can then align the unmapped BAM file to TE

690 consensus to create CpG methylation pileup results.

691 To calculate average methylation of certain regions, we extracted methylation prediction

692 value of each CpG site of each read from bam files with methylation tags with a python

script (python bam.Mmtag.regions.oo.py -b <bam> -r <insertion.bed> -o

<ins.methylC.reldist.txt> -f <bed>) available in Github

repository(https://github.com/xzhuo/modbamUtil)

To evaluate the relationship between CpG methylation and indels, we aggregated

methylation prediction of all 32 samples and calculated the average CpG methylation of

each CpG Island (CGI)[61].

Insertion and flanking methylation calculation

700   We selected non-reference insertions from annotated SVs and used a custom python script

701   in the Github repository(https://github.com/xzhuo/modbamUtil) to calculate average

702   methylation of the insertion and flanking regions (python read.methylation.mean.py -i

703   <input> -o <output> -s <start> -l <length> -c). Two-sided F-test were performed to

704   compare methylation variation.

CpG island methylation and INDEL frequency calculation

Unmasked CpG island annotation file was downloaded from UCSC

(https://hgdownload.soe.ucsc.edu/goldenPath/hg38/database/cpgIslandExtUnmasked.txt

.gz). For each CpG site on hg38, we calculated the median methylation percentage of the 32

HiFi methylation. We then calculated the average methylation percentage of each CpG

island using the median methylation.

After separating CpG islands to hypermethylated and hypomethylated ones using 50%

methylation as cut-off, we calculated the INDEL frequency of different sizes within CpG

islands. To create the background INDEL frequency in the genome, we shuffled CpG islands

in the genome and repeated the calculation. INDEL frequency difference were compared

using two-sided t-test.

We also repeated the same calculation using same methylation data and INDEL callset from

1000 genome project and HGSVC project[44,45].

Ethics and Inclusion statement

The research is conceptualized and conducted by the colleagues from Washington

University and HPRC consortium using both publicly available and newly generated data.

Being a study about overall human population, it is not locally relevant. All results and raw

data would be open to public upon publication.

Data availability statement

HiFi reads with methylation are available at https://s3-us-west-2.amazonaws.com/human-

pangenomics/index.html?prefix=submissions/560047a6-6d16-4b0c-aac9-7d0c83e2188e-

-HIFI-METHYLATION-READS/.

ONT reads are available at https://s3-us-west-2.amazonaws.com/human-

pangenomics/index.html?prefix=submissions/CBC1E2D6-3925-4CD0-9682-

555C64F81B02--UCSC_HPRC_ONT_Y1_WTOPUP_GUPPY6/.

Variants calls of the same individuals were available at https://s3-us-west-

2.amazonaws.com/human-pangenomics/index.html?prefix=submissions/B581EBA7-

8BDE-4C7C-9DEA-78B99A051155--Yale_HPP_Year1_Variant_Calls/.

WGBS illumina reads will be make available at NIH GEO dataset GSE261315.

Processed data mapped to either hg38 or individual assemblies are available in datahub

provided above in the "individual genome hub" session.

Code availability

All custom scripts used in the manuscript are available at

https://github.com/xzhuo/modbamUtil.

Reference

1.   Bird, A. P. CpG-rich islands and the function of DNA methylation. *Nature* **321**, 209–

213 (1986).

2.   The ENCODE Project Consortium. An integrated encyclopedia of DNA elements in

the human genome. *Nature* **489**, 57–74 (2012).

3.   Roadmap Epigenomics Consortium *et al.* Integrative analysis of 111 reference

human epigenomes. *Nature* **518**, 317–330 (2015).

4.   Moore, L. D., Le, T. & Fan, G. DNA Methylation and Its Basic Function.

Neuropsychopharmacol **38**, 23–38 (2013).

5.   Jones, P. A. Functions of DNA methylation: islands, start sites, gene bodies and

beyond. *Nat Rev Genet* **13**, 484–492 (2012).

6.   Smith, Z. D., Hetzel, S. & Meissner, A. DNA methylation in mammalian development

and disease. *Nat Rev Genet* (2024) doi:10.1038/s41576-024-00760-8.

7.   Sved, J. & Bird, A. The expected equilibrium of the CpG dinucleotide in vertebrate

genomes under a mutation model. *Proceedings of the National Academy of Sciences of the*

United States of America **87**, 4692–4696 (1990).

8.   Han, L., Su, B., Li, W.-H. & Zhao, Z. CpG island density and its correlations with

genomic features in mammalian genomes. *Genome Biology* **9**, R79 (2008).

9.   Turker, M. S. The establishment and maintenance of DNA methylation patterns in

mouse somatic cells. *Seminars in Cancer Biology* **9**, 329–337 (1999).

10.   Turker, M. S. Gene silencing in mammalian cells and the spread of DNA methylation.

Oncogene **21**, 5388–5393 (2002).

11.   Sentmanat, M. F. & Elgin, S. C. R. Ectopic assembly of heterochromatin in Drosophila

melanogaster triggered by transposable elements. *Proceedings of the National Academy of*

Sciences **109**, 14104–14109 (2012).

12.   Zhou, W., Liang, G., Molloy, P. L. & Jones, P. A. DNA methylation enables transposable

element-driven genome expansion. *PNAS* **117**, 19359–19366 (2020).

13.   Hodges, E. *et al.* High definition profiling of mammalian DNA methylation by array

capture and single molecule bisulfite sequencing. *Genome Res.* **19**, 1593–1605 (2009).

14.   Weber, M. *et al.* Chromosome-wide and promoter-specific analyses identify sites of

differential DNA methylation in normal and transformed human cells. *Nat Genet* **37**, 853–

862 (2005).

15.   Meissner, A. *et al.* Genome-scale DNA methylation maps of pluripotent and

differentiated cells. *Nature* **454**, 766–770 (2008).

16.   Maunakea, A. K. *et al.* Conserved role of intragenic DNA methylation in regulating

alternative promoters. *Nature* **466**, 253–257 (2010).

17.   Lister, R. *et al.* Human DNA methylomes at base resolution show widespread

epigenomic differences. *Nature* **462**, 315–322 (2009).

18.   Cokus, S. J. *et al.* Shotgun bisulphite sequencing of the Arabidopsis genome reveals

DNA methylation patterning. *Nature* **452**, 215–219 (2008).

19.   Laurent, L. *et al.* Dynamic changes in the human methylome during differentiation.

Genome Res. **20**, 320–331 (2010).

20.   Vaisvila, R. *et al.* Enzymatic methyl sequencing detects DNA methylation at single-

base resolution from picograms of DNA. *Genome Res.* **31**, 1280–1289 (2021).

21.   Nunn, A., Otto, C., Fasold, M., Stadler, P. F. & Langenberger, D. Manipulating base

quality scores enables variant calling from bisulfite sequencing alignments using

conventional bayesian approaches. *BMC Genomics* **23**, 477 (2022).

22.   van Dijk, E. L., Jaszczyszyn, Y., Naquin, D. & Thermes, C. The Third Revolution in

Sequencing Technology. *Trends in Genetics* **34**, 666–681 (2018).

23.   Sigurpalsdottir, B. D. *et al.* A comparison of methods for detecting DNA methylation

from long-read sequencing of human genomes. *Genome Biol* **25**, 69 (2024).

24.   Flusberg, B. A. *et al.* Direct detection of DNA methylation during single-molecule,

real-time sequencing. *Nat Methods* **7**, 461–465 (2010).

25.   Schatz, M. C. Nanopore sequencing meets epigenetics. *Nat Methods* **14**, 347–348

(2017).

26.   Tse, O. Y. O. *et al.* Genome-wide detection of cytosine methylation by single molecule

real-time sequencing. *PNAS* **118**, (2021).

27.   Ni, P. *et al.* DNA 5-methylcytosine detection and methylation phasing using PacBio

circular consensus sequencing. 2022.02.26.482074 Preprint at

https://doi.org/10.1101/2022.02.26.482074 (2022).

28.   Liu, Y. *et al.* DNA methylation-calling tools for Oxford Nanopore sequencing: a

survey and human epigenome-wide evaluation. *Genome Biology* **22**, 295 (2021).

29.   Gerdes, P. *et al.* Locus-resolution analysis of L1 regulation and retrotransposition

potential in mouse embryonic development. *Genome Res.* (2023)

doi:10.1101/gr.278003.123.

30.   Bodea, G. O. *et al.* LINE-1 retrotransposons contribute to mouse PV interneuron

development. *Nat Neurosci* 1–11 (2024) doi:10.1038/s41593-024-01650-2.

31.   Liao, W.-W. *et al.* A draft human pangenome reference. *Nature* **617**, 312–324 (2023).

32.   Ernst, J. & Kellis, M. ChromHMM: automating chromatin-state discovery and

characterization. *Nature methods* **9**, 215–216 (2012).

33.   Wu, H. *et al.* Detection of differentially methylated regions from whole-genome

bisulfite sequencing data without replicates. *Nucleic Acids Res* **43**, e141 (2015).

34.   Chu, C. *et al.* Comprehensive identification of transposable element insertions using

multiple sequencing technologies. *Nat Commun* **12**, 3836 (2021).

35.   Zhuo, X. *et al.* Comparing genomic and epigenomic features across species using the

WashU Comparative Epigenome Browser. *Genome Res.* **33**, 824–835 (2023).

36.   Zhou, X., Li, D., Lowdon, R. F., Costello, J. F. & Wang, T. methylC Track: visual

integration of single-base resolution DNA methylation data on the WashU EpiGenome

Browser. *Bioinformatics* **30**, 2206–2207 (2014).

37.   Li, D., Zhuo, X., Harrison, J. K., Liu, S. & Wang, T. Modbed track: Visualization of

modified bases in single-molecule sequencing. *Cell Genomics* **3**, 100455 (2023).

38.   Zhang, Y. *et al.* Repetitive elements and enforced transcriptional repression co-

operate to enhance DNA methylation spreading into a promoter CpG-island. *Nucleic Acids*

Research **40**, 7257–7268 (2012).

39.   Lee, Y., Lee, J., Kim, J. & Kim, Y.-J. Insertion variants missing in the human reference

genome are widespread among human populations. *BMC Biology* **18**, 167 (2020).

40.   Batzer, M. A. & Deininger, P. L. Alu repeats and human genomic diversity. *Nature*

Reviews Genetics **3**, 370–379 (2002).

41.   Coulondre, C., Miller, J. H., Farabaugh, P. J. & Gilbert, W. Molecular basis of base

substitution hotspots in Escherichia coli. *Nature* **274**, 775–780 (1978).

42.   Zhuo, X., Du, A. Y., Pehrsson, E. C., Li, D. & Wang, T. Epigenomic differences in the

human and chimpanzee genomes are associated with structural variation. *Genome Res.* **31**,

279–290 (2021).

43.   Deaton, A. M. & Bird, A. CpG islands and the regulation of transcription. *Genes &*

development **25**, 1010–1022 (2011).

44.   The 1000 Genomes Project Consortium. A global reference for human genetic

variation. *Nature* **526**, 68–74 (2015).

45.   Ebert, P. *et al.* Haplotype-resolved diverse human genomes and integrated analysis

of structural variation. *Science* **372**, eabf7117 (2021).

46.   Lanciano, S. *et al.* Locus-level L1 DNA methylation profiling reveals the epigenetic

and transcriptional interplay between L1s and their integration sites. *Cell Genomics* **4**,

100498 (2024).

47.   Li, D. *et al.* WashU Epigenome Browser update 2022. *Nucleic Acids Research* **50**,

W774–W781 (2022).

48.   Cheng, H., Concepcion, G. T., Feng, X., Zhang, H. & Li, H. Haplotype-resolved de novo

assembly using phased assembly graphs with hifiasm. *Nat Methods* **18**, 170–175 (2021).

49.   Alonge, M. *et al.* Automated assembly scaffolding using RagTag elevates a new

tomato system for high-throughput genome editing. *Genome Biology* **23**, 258 (2022).

50.   Lam, E. T. *et al.* Genome mapping on nanochannel arrays for structural variation

analysis and sequence assembly. *Nat Biotechnol* **30**, 771–776 (2012).

51.   Li, H. New strategies to improve minimap2 alignment accuracy. *Bioinformatics* **37**,

4572–4574 (2021).

52.   Krueger, F. & Andrews, S. R. Bismark: a flexible aligner and methylation caller for

Bisulfite-Seq applications. *Bioinformatics* **27**, 1571–1572 (2011).

53.   Lee, H. J. *et al.* Regenerating zebrafish fin epigenome is characterized by stable

lineage-specific DNA methylation and dynamic chromatin accessibility. *Genome Biology* **21**,

52 (2020).

54.   Wickham, H. *ggplot2*. (Springer Science & Business Media, New York, NY, 2009).

doi:10.1007/978-0-387-98141-3.

55.   Emerson, J. W. *et al.* The Generalized Pairs Plot. *Journal of Computational and*

Graphical Statistics **22**, 79–91 (2013).

56.   Feng, H., Conneely, K. N. & Wu, H. A Bayesian hierarchical model to detect

differentially methylated loci from single nucleotide resolution sequencing data. *Nucleic*

Acids Res **42**, e69 (2014).

57.   Holt, J. M. *et al.* HiPhase: jointly phasing small, structural, and tandem repeat

variants from HiFi sequencing. *Bioinformatics* **40**, btae042 (2024).

58.   Patterson, M. *et al.* WhatsHap: Weighted Haplotype Assembly for Future-Generation

Sequencing Reads. *Journal of Computational Biology* **22**, 498–509 (2015).

59.   Li, H. *et al.* A synthetic-diploid benchmark for accurate variant-calling evaluation.

Nat Methods **15**, 595–597 (2018).

60. Li, H. Minimap2: pairwise alignment for nucleotide sequences. *Bioinformatics* **34**,

3094–3100 (2018).

61. Quinlan, A. R. & Hall, I. M. BEDTools: a flexible suite of utilities for comparing

genomic features. *Bioinformatics* **26**, 841–842 (2010).

a Cytosine methylation calling of five lymphoblastoid cell lines

b hg38:chr17:7682000-7695000

c HG00741 whole genome methylation correlation

d

e

f Falsely discovered DMRs between different methods

a

Average Flanking Methylation

Reference Genome

-300bp   +300bp

Insertion → Average Insertion Methylation

b All non-reference insertions

Slope = 0.87, $R^2 = 0.59$
Slope = 0.14, $R^2 = 0.032$
Slope = 0.21, $R^2 = 0.12$
Slope = 0.19, $R^2 = 0.12$
Slope = 0.20, $R^2 = 0.08$

Insertion type
- non-TE
- *Alu*
- LTR
- LINE1
- SVA

Average insertion methylation (y-axis)
Average flanking methylation (x-axis)

c

Average Flanking Methylation

CpG Island

Reference Genome

-300bp   +300bp

Insertion → Average Insertion Methylation

d Non-reference insertions within CpG islands

Slope = 0.89, $R^2 = 0.6$
Slope = 0.97, $R^2 = 0.89$

Average insertion methylation (y-axis)
Average flanking methylation (x-axis)

e hg38:chr1:8382000-8391000

Gene — RERE
RepeatMasker
WGBS
maternal_HiFi
maternal_HiFi
maternal_ONT
maternal_ONT
paternal_HiFi
paternal_HiFi
paternal_ONT
paternal_ONT
HG03516
HG00621
WGBS
maternal_HiFi
maternal_HiFi
maternal_ONT
maternal_ONT
paternal_HiFi
paternal_HiFi
paternal_ONT

f hg38:chr11:59561000-59571000

RepeatMasker
CpG Island
maternal_HiFi
maternal_HiFi
maternal_ONT
maternal_ONT
HG03516_maternal
HG03516_paternal
paternal_HiFi
paternal_HiFi
paternal_ONT
paternal_ONT

g

10kb 9.9kb 9.8kb ... 100bp 0bp 100bp ...9.9kb 10kb

insertion 1
insertion 2
insertion 3
insertion 4
all insertions

methylation correlation slope

h

Methylation correlation slope (y-axis)
Relative position to the insertion site (x-axis)

non-TE | *Alu* | LTR
LINE1 | SVA

Insertion type
- non-TE
- *Alu*
- LTR
- LINE1
- SVA

i

Methylation correlation slope (y-axis)
Relative position to the insertion site (x-axis)

30 - 100 | 100 - 300 | 300 - 1000
1000 - 3000 | 3000 - 1000

a

Empty Flanking
Methylation level of 300bp flanking region

Reference Allele

-300bp +300bp

Insertion Allele

Insertion

Insertion
Methylation level of insertion

Insertion Flanking
Methylation level of 300bp flanking region of insertion

Flanking Methylation Difference = Insertion Flanking - Empty Flanking

b

Methylation level of non-TE insertion, insertion flanking, and empty flanking

Insertion methylation level

c

Methylation level of TE insertion, insertion flanking, and empty flanking

Alu   LTR

LINE1   SVA

Insertion methylation level

d

-25%   0.25%   +25%

99%

e

4.0%
3.2%
0.3%
1.7%

-25%   +25%

96%

TE
Alu
LTR
LINE1
SVA

a HiFi (32 samples) **b** ONT (5 samples) **c** WGBS (5 samples)

relative position to insertion sites

d hg38:chr1:40055000-40063000

e hg38:chr1:40058800-40059500

Zoom in