Methylation patterns reveal cryptic structure and a pathway for adaptation in a panmictic carnivore

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Summary

Determining molecular signatures of population divergence is a fundamental component of evolutionary biology. Identifying divergence is particularly challenging between populations of highly mobile species that undergo substantial gene flow, such as the Canada lynx (*Lynx canadensis*), where populations are considered panmictic when only neutral genetic markers are considered. Here, we used high-throughput bisulfite sequencing to examine the environmental determinants of methylation structure across the distributional range of Canada lynx. Despite a high degree of genetic similarity among mainland populations, epigenetic structure did not mirror these neutral patterns, instead showing environmental associations and high levels of divergence in the peripheral Newfoundland and Alaskan populations. Interestingly, a disproportionate number of genes related to body-size were hypermethylated on the island of Newfoundland, providing a possible mechanism for adaptive evolution and the observed island effect on organism size. Our results indicate that epigenetic modifications, specifically DNA methylation, are powerful markers to investigate adaptive divergence and rapid evolutionary response.

Keywords: Ecological genetics, genomics / methylomics, adaptation, non-model organisms

Background

Investigations into divergent selection have often relied on quantifying phenotypic variation and the heritability of such traits, the latter assumed to be genetic polymorphisms transmitted via an organism's DNA[1]. However, detecting adaptive divergence in species that experience high rates of gene flow is challenging due to the homogenization of genomic regions that are neutral or under weak selection[2]. Environmental conditions can be a powerful driver of adaptive divergence, where relationships are traditionally ascertained by correlating allele frequencies to environmental variation[3]. An aspect of adaptive molecular evolution that is undetected by standard genetic sequencing involves direct modifications to the structure of DNA. Epigenetic modifications like DNA methylation are influenced by environmental conditions, directly affect gene expression, and may be indicative of early adaptive divergence due to local adaptation[4–6]. DNA methylation could play a role in local adaptation due to its regulatory role in transcription by modifying chromatin structure, repressing transcription factors, or recruiting protein complexes that block transcriptional machinery, especially around CpG islands[7–9]. CpG islands are dense clusters of cytosine-guanine dinucleotides and frequently occur near the transcription start site of genes and have functional role with gene expression[10–12]. Consequently, DNA methylation, especially around CpG islands, could explain the molecular basis of local adaptation due to its regulatory function on gene expression, and might be an overlooked molecular marker of adaptive divergence and rapid evolutionary adaptation.

Here, we assessed whether environmental variation, geographic distance, or insularity were determinants of DNA methylation structure in a free-ranging carnivore. Our study species, the Canada lynx, (*Lynx canadensis*) is a mid-sized felid that is highly mobile and whose neutral genetic variation (i.e., microsatellites) exhibits low levels of genetic differentiation across the mainland, with divergent island populations[13,14]. Despite this low degree of overall genetic structure, two potential mechanisms might drive epigenetic divergence in Canada lynx. First,

allele frequencies are correlated to climatic gradients in both population time-series and fine-scale genetic analyses[13,15,16], suggesting climate might also influence patterns of methylation in lynx. Second, Canada lynx show a subtle cline in body size with larger individuals in Alaska[17] to smaller individuals in insular populations including Newfoundland and Cape Breton Island[18]. Body size changes in island populations appear to be consistent with the 'Island Rule'[18], where insular mammals are smaller in size compared to their mainland counterparts[19–22]. If functional genes related to body size are repressed in geographically isolated populations, then epigenetic modifications might be an underlying mechanism driving population divergence[23]. Based on these two mechanisms (climate and island isolation), we tested two predictions: i) climatic conditions are the driving force behind spatial epigenetic structuring[24]; and ii) patterns of DNA methylation over CpG islands and gene bodies are more correlated with biogeographical substructuring than methylation patterns over DNA of unknown function, due to the regulation of transcription arising from adaptation to local conditions[25].

Results

We identified differential methylation at base-pair resolution across the genome in 95 Canada lynx epidermal tissue samples from four populations (n = 23-24 per sampling area) across North America, including one insular population in Newfoundland (Figure 1; Supplemental Table S4). The sampled populations have a wide geographical spread, with an average minimum distance between populations (Québec and Newfoundland) of 1,158 km and a maximum distance (Alaska and Newfoundland) of 5,520 km. Habitats around these populations present a dynamic range of environmental conditions, ranging from 32 to 432 mm of winter precipitation and a mean annual temperature range[26] of -6.3 to 4.7° C. To determine associations between these environmental conditions and genome-wide patterns of DNA methylation, we created a reduced representation bisulfite sequencing (RRBS) library (full protocol in Supplemental). Paired-end sequencing on a HiSeq2500 generated a total of 210,773,612 filtered and demultiplexed reads

that were aligned to the domestic cat genome (85.0% average mapping success; Supplemental Table S4; *Felis catus*; NCBI felcat9.0) and variants were called using specially designed software for bisulfite converted reads[27]. We mapped our reads to the human (*Homo sapiens*) and lambda phage genomes to rule out contamination (2.7% and <0.1% success, respectively), and assessed bisulfite conversion efficiency by including non-methylated lambda phage DNA in the sequencing lane. Furthermore, we quantified the temporal effects of methylation, the ramifications of missing data, and model parameterization with sensitivity analyses, with no implications on overall inferences (Supplemental Figures S5-S8).

Pronounced population structure revealed by methylation patterns

To examine regions with putative regulatory function, CpG islands were first bioinformatically identified *de novo* (N = 28,127) using hidden Markov models and contained an average GC content of 59.2% with a posterior probability of observed-to-expected GC content ($CpG_{o/e}$) of 1.13. Our DNA methylation analysis was broken into two subsets based on proximity to genomic features, with identical filtering parameters for each subset to maximize comparative inferences. Our subset over CpG islands and gene bodies contained 329 5kb windows with 4,611 CpG positions, while the unannotated dataset contained 376 kb windows with 5,031 CpG positions (Supplemental Table S6). Qualitatively, population structure was most pronounced in DNA methylation patterns over CpG islands and gene bodies compared to methylation patterns over regions of unknown function. The first two axes of a principal coordinates analysis (PCoA) on a Euclidean distance matrix summarizing CpG island and gene body methylation (PCoA1 = 6.2%, PCoA2 = 5.0% variation explained) distinctly cluster Alaska from the remaining mainland populations (Figure 2). Similar, but less distinct patterns were seen in the ordination of methylation patterns over unannotated regions of the genome (Figure 2). Analogous population-level trends between the datasets were further confirmed with Pearson and Spearman's rank coefficients of the first PCoA axis ($r = 0.91$; $\rho = 0.88$).

Environmental variation associated with epigenetic structure

For both methylation datasets, model selection identified three significant variables in our db-RDA analysis: geographic distance, climate and a binary variable representing insularity for the Newfoundland population (pseudo-***F*** = 16.26 - 16.27; adjusted R^2 = 0.33; all p = 0.001). Tree cover (p = 0.13 - 0.50) and a randomly-generated numeric variable to assess the effect of noise (p = 0.64 – 0.78) added no explanatory power to either model (Supplemental Table S11). Collinearity was low between all retained variables (VIF = 2.09 – 3.77; Supplemental Table S12). We examined the explanatory power of each variable independently using partial db-RDAs (Figure 4), which revealed similar trends between both methylation datasets for geographic distance (pseudo-***F*** = 15.72 – 17.47; adjusted R^2 = 0.11 – 0.12; p = 0.001) and climate (pseudo-***F*** = 6.75 – 6.90; adjusted R^2 = 0.04; p = 0.001). However, methylation patterns over CpG islands and gene bodies were more strongly associated with the insular Newfoundland population (pseudo-***F*** = 13.66; adjusted R^2 = 0.09; p = 0.001) than with methylation patterns over unannotated regions (pseudo-***F*** = 10.03; adjusted R^2 = 0.07; p = 0.001), suggesting stronger epigenetic divergence in putatively regulatory regions of the genome in insular Canada lynx (Figure 3).

Differential methylation over genes related to morphology

We identified differential methylation directly over CpG islands and gene bodies using beta regressions (n = 329), with population as an explanatory variable (i.e. windows with > 10% overall difference in methylation and p-value < 0.001). Of the 16 gene regions identified, 11 were significantly differentiated in the Newfoundland population (Table 1). All differentially methylated regions with associated morphological function were hypermethylated, as well as genes with direct epigenetic function with morphological interactions (i.e. transcription regulation, DNA-binding transcription factors; Table 1). The 11 differentially methylated regions in the insular population have a difference in methylation of 14%-40% compared to mainland

populations, which suggests that morphological divergence in the insular population might be regulated by repressed gene expression due to DNA methylation. Additionally, we identified three differentially methylated regions in the Alaskan population related to spectrin, carbohydrate, and ATP binding, suggesting differential expression of genes with metabolic function.

Genetic structure driven by insular and climatic divides

We examined the relationship between neutral SNPs, environmental variation, geographic distance, and insularity by first performing a principal coordinates analysis on a Euclidean distance dissimilarity matrix of 489 genomic SNPs identified using a Bayesian wildcard algorithm with conservative calling and filtering parameters[28]. Consistent with previous research on population structure in Canada lynx[13,29], our SNP data analysis indicated substantial genetic separation of the insular Newfoundland population (F_{ST} = 0.10 – 0.13). We complemented our F_{ST} analysis with a null model approach that calculated the relative differentiation between populations, and mainland populations were relatively similar (F_{ST} = 0.005 – 0.024) with Newfoundland as the most segregated (F_{ST} = 0.096). Consistent with previous research[14], gene diversity was lowest in the Newfoundland population (H_e = 0.224). An analysis of molecular variance (AMOVA) identified substantial genetic variation between populations, which explained 8.58% of the total variation in SNP data (σ = 5.84, p = 0.01). Outlier detection with Bayescan v2.0[30] (false discovery rate > 0.05) identified no loci under selection.

We determined relationships between genetic data and environmental variables by performing a db-RDA step-wise model selection on the retained PCoA axes, and identified only climate (pseudo-***F*** = 51.13; p-value = 0.001) and insularity (pseudo-***F*** = 26.33; p-value = 0.001) as important for explaining genetic variation (Supplemental Figure S11). Geographic distance (p-value = 0.31), tree cover (p-value = 0.95), and the randomly generated numeric variable (p-value = 0.33) were all dropped during the model step-selection. The first axis of the db-RDA

was strongly representative of both climate (db-RDA1 = -0.86) and insularity (db-RDA1 = 0.99), while the second axis primarily summarized genetic variation associated with climate (db-RDA2 = 0.51). Partial db-RDAs identified a substantial amount of the net variation was explained by the mainland – Newfoundland divide (pseudo-***F*** = 26.3; adjusted R^2 = 0.15; p-value = 0.001), while climatic variation explained much of the variation seen in mainland populations (pseudo-***F*** = 13.70; adj. R^2 = 0.08; p-value = 0.001). We identified a stronger correlation between SNP data and non-coding region methylation (r = -0.78; ρ = -0.62) than with CpG island and gene body methylation (r = -0.74; ρ = -0.61) from the first axes of PCoAs using Pearson's and Spearman's ranking coefficients, respectively.

Discussion

A new chapter in Canada lynx population structure

We have shown that despite seemingly panmictic populations across the mainland at the genetic level, epigenetic structure is substantial and might be an underlying mechanism driving local adaptation. Row et al. showed a minimal barrier effect of the Rocky Mountains to Canada lynx[13], but it remains possible that distinct environmental variation might be driving unique patterns of functionally important DNA methylation at the range margins, including Alaska and Newfoundland. Despite the lack of genetic structure between mainland populations[29], we see distinct patterns of DNA methylation that differentiate Alaska from mid- and east-continental populations. Furthermore, we identified variation that is associated by trends in winter precipitation and temperature that is not accounted for by geographic distance.

The differentiated DNA methylation patterns in the Newfoundland population suggest a molecular pathway for morphological differences between mainland and island populations, as predicted by the Island Rule. Evidence for this adaptive divergence was observed in disparities between methylation in CpG islands/gene bodies and DNA of unknown function and specific

genes. We identified specific genes (ZEB1 and HDAC9) that may underlie differences in body size between mainland and Newfoundland lynx. The hypermethylated HDAC9 gene is of particular interest because downregulation in HDAC9 is associated with diminished body mass[31]. Commonly, insular mammalian carnivores are smaller in size[22], which is consistent with existing data on the insular population of Canada lynx[17,18].

An overlooked marker for examining rapid evolution and adaptive divergence

Our results indicate that DNA methylation can detect population divergence despite substantial gene flow, and can be a powerful marker to examine cryptic population structure in species that seem genetically panmictic. Identifying the molecular basis of adaptive divergence between populations has relied on comparing allele frequencies or isolating outlier loci under selection[32,33]. These results suggest that epigenetic modifications increase resolution when defining population structure and are a useful marker for examining subtle differentiation. With time, divergent methylation patterns should lead linked SNPs to act as if under directional selection, and thus could be factored into the working model of speciation[2]. Divergent methylation patterns also have implications for conservation. For example, seemingly genetically homogenous individuals could be epigenetically adapted to local conditions[34], and thus, greater care would be needed to select individuals for translocations[35]. These results indicate that epigenetic modifications play a role in defining population structure, with a putative relationship to adaptation.

For decades, the adaptive role of epigenetic modifications in evolution has been controversial[36–38]. Our data provide evidence that epigenetic modifications are a mechanism underlying rapid evolutionary change. The evolutionary history of Canada lynx on Newfoundland is unclear, yet evidence suggests post-glacial colonization (10,000 years)[13]. The disproportionate levels of differential methylation in the smaller Newfoundland lynx, particularly over genes with morphological significance, suggest an epigenetic pathway for rapid

evolutionary responses to geographic isolation[36]. Insular populations of mammals generally have notable phenotypic differentiation[22,39], and DNA methylation serves as a potential mechanism driving insular phenotypic divergence due to its plasticity to environmental conditions[40]. Collectively, our results suggest that epigenetic modifications like DNA methylation are an overlooked molecular signature of population divergence and local adaptation, and offer a putative mechanism underlying rapid evolutionary response.

Methods

Sample Acquisition and Reduced-Representation Bisulfite Sequencing (RRBS) Library Preparation

Georeferenced Canada lynx tissue samples were collected from fur auction houses throughout eastern North America from dried pelts (North American Fur Auctions, Fur Harvester's Auctions, Inc.). Individuals from four geographic locations were chosen for this study, spanning the longitudinal and latitudinal range of the species and consistent with previous research on the Canada lynx system (Rueness et al 2003). Tissue was consistently taken from the same morphological location from each adult-sized pelt. Genomic DNA was isolated using a MagneSil® (Promega Corporation) Blood Genomic Max Yield System a JANUS® workstation (PerkinElmer, Inc.) and quantified and standardized to 20 ng/µl with a Quant-iT PicoGreen® ds-DNA assay using manufacturer's instructions (Thermo Fisher Scientific). We adapted an existing reduced representation bisulfite sequencing library preparation workflow designed for multiplexed high-throughput sequencing[41]. Genomic DNA (400 ng) for 95 Canada lynx samples was digested with NsiI and AseI restriction enzymes overnight and subsequently ligated with methylated adapters (Supplemental Table S1). An individual sample of completely non-methylated lambda phage genomic DNA (200 ng; Sigma-Aldrich – D3654) with a unique barcode was included to assess bisulfite conversion efficiency (Supplemental Table S7). Barcoded samples were then combined into eight pools to ensure consistent reaction

environments for the entire library using a QIAquick PCR Purification Kit (Qiagen, Valencia, CA, USA) following manufacturer's instructions and 10 µL of 3M NaAc was added to neutralize pH. We then performed a SPRI size selection on each pool (0.8x volume ratio) with Agencourt® AMPure® XP beads (Beckman Coulter, Inc.). Nicks between the 3' fragment overhang and the 5' non-phosphorylated adapter nucleotide were repaired with DNA polymerase I and bisulfite conversion was performed on each pool using an EZ DNA Methylation-Lightning Kit™ (Zymo Research) with a 20-minute desulphonation time.

Pools were amplified in three separate PCRs to mitigate stochastic differences in amplification and were subsequently concentrated using a QIAquick PCR Purification Kit (Qiagen, Valencia, CA, USA). The eight pools were quantified with Qubit 3.0® (Thermo Fisher Scientific) and appropriate amounts were added to a final super-pool for equal weighting. A final magnetic bead clean-up (0.8x volume ratio) was performed to remove any adapter dimer. We checked final library concentration and fragment distribution with a Qubit® 3.0 (ThermoFisher Scientific) and Hi-Sense Bioanalyzer 2100 chip (Agilent), respectively. Paired-end 125-bp sequencing was performed on a single lane on an Illumina HiSeq 2500 platform at the Centre for Applied Genomics at the Hospital for Sick Children (Toronto, Ontario, Canada). Raw sequence data FastQ files are available on the Sequence Read Archive (ID Pending).

Bioinformatics – quality checks and SNP calling

We assessed sequencing success as well as removed adapter and low-quality reads via FastQC[42] (Andrews, 2010) and Cutadapt[43] implemented in Trim_Galore! V0.4.4[44] (Krueger, 2014). Individuals were demultiplexed using python scripts[41]. Paired-ends reads for Canada lynx samples were initially aligned to several genomes (*Felis catus, Homo sapiens,* Lambda Phage) using Bismark[27] to assess mapping efficiency and contamination (Supplemental Table S4). Paired-end reads for downstream analyses were aligned to the domestic cat genome with Bismark, using relaxed mapping parameters (score_min L,0,-0.6)[27].

SNPs were called from indexed BAM files with CGmapTools[28] using a coupled Bayesian wildcard algorithm with a conservative 0.01 error rate and a static 0.001 p-value for calling variant sites, which generated variant call files (VCFs). VCF files were indexed, merged, and filtered using VCFtools[45] for bi-allelic loci with a sequencing depth of at least five, and were shared between at least 50% of the individuals (max-missing 0.5) and a minor allele frequency (maf) of > 0.001. Sites were further filtered by removing any variants out of Hardy-Weinberg equilibrium within populations (p-value < 0.05). A pair-wise Euclidean dissimilarity (distance) matrix was computed on the SNP data using the function *daisy* within the package *cluster*[46] using R v3.4.2[47]. This dissimilarity matrix was then summarized in a principal coordinates analysis (PCoA) using the *dudi.pco* function in *adegenet*[48]. Missing SNP data was imputed by mean allele at a population level. Pairwise F_{ST} was calculated using StAMPP (Supplemental Figure S2) and relative F_{ST} was measured using a null model Bayesian approach implemented in BayeScan v2.0[30] (Supplemental Figure S2). AMOVA between populations was computed using the *poppr.amova* function within *poppr*[49], and heterozygosity was assessed with *adegenet.*

Bioinformatics – DNA methylation

We identified methylated and non-methylated positions by first filtering BAM files for incomplete bisulfite conversion based on reads containing more than three methylated positions in a CHH or CHG context. In the remaining reads, methylated positions in a CpG context with a sequencing depth of at least five were extracted with Bismark[27], truncating the last two bases of the forward mate-paired reads (R1) and the first two bases of the reverse mate-paired (R2) reads. Methylation polymorphisms in areas of overlap between read pairs were extracted only once. After confirming that our non-directional library contained roughly equal reads for all possible amplified DNA strands, we proceeded to analysis.

We first generated a custom CpG island annotation track using hidden Markov models based on $CpG_{o/e}$ implemented in *makeCGI*[50]. Only islands with a calculated posterior probability greater than 99.5% were retained for analysis, based on $CpG_{o/e}$. Mapped and extracted methylated sites were then imported into Seqmonk[51] using the generic text importer, and raw data was qualitatively visualized against the annotated domestic cat genome (felCat9.0). We analyzed DNA methylation over CpG islands and gene bodies by creating 5,000-bp running windows directly over and 25,000-bp upstream of gene bodies, combined with windows directly over CpG islands. Each window was assigned a methylated percentage score based on the overall ratio of methylated to non-methylated bases within the feature. We filtered this window-set for regions that had at least one CpG and equal representation from each population. This process was repeated for our second subset of analyses that investigated methylation patterns of unannotated regions of the genome. For this analysis, we created 5,000-bp running windows across the entire genome and removed any windows that overlapped with the initial windows over CpG islands and gene bodies by more than 1%. Data was filtered, exported, and summarized in the same way as the first analysis.

Sensitivity analyses

To determine the implications of missing data and PCoA axis retention thresholds, we performed two sensitivity analyses. The first analysis examined the effects of missing data by repeating all analyses using a subset of the top 10 individuals per population (N = 40), and again with the top 6 individuals per population (N = 24), across all three datasets (Supplemental Figure S5-S6, Table S8). Overall trends in explanatory effects (adjusted R^2) and qualitative inferences (PCoA clustering) were investigated and no change in inferences were determined. We examined the implications of arbitrary PCoA axis retention by repeating all analyses, but instead using different cumulative variation explained thresholds as response variables. We performed a number of db-RDAs using all axes explaining 30%, 50%, 75%, and 95%

cumulative variation as response variables, and results were qualitatively similar regardless of axis retention (Supplemental Figure S8, Table S10).

Quantifying environmental associations

To determine if patterns of DNA methylation and genomic variability could be explained by macro-scale climatic conditions, geographic distance, or insular divergence, we performed a distanced-based redundancy analysis on the summarized SNP and DNA methylation data. Meaningful axes explaining > 30% of the cumulative variation in the data were used as response variables in a distance-based redundancy analysis (db-RDA) conducted in *vegan*[52], using variables that putatively describe the environmental determinants of population structure in Canada lynx. Our covariates included a binary variable of insularity, which identified the Newfoundland population against mainland populations and was used to describe the largely impassable barrier of the Strait of Belle Isle between Newfoundland and mainland Labrador[53]. A variable of geographic distance was included which was simply the first axis of a principal coordinates analysis (PCoA) on a Euclidean distance matrix of latitude and longitude (PCo1 = 99.7% of the variation). In addition to the geographic variables, we included a biotic variable of percent tree cover[54], a randomly generated numerical variable to assess the effect of noise, and a climate variable. For the climate variable, we performed a PCA on climate data to prevent multi-collinearity, which reduced annual temperature ranges, winter precipitation, and minimum coldest temperature to a single PCA axis[26] (PC1 = 85.6% of the variation). Linearity was confirmed between response and explanatory variables, and multi-collinearity between explanatory variables was assessed using the VIF and any variables > 4 were removed (Supplemental Table S12). Step-wise model selection using the function *ordistep* within *vegan*[52] was performed to isolate the best overall model using a QR decomposition technique based on p-values (Supplemental Table S11). To isolate the individual explanatory power of each

variable, we performed partial distanced-based redundancy analyses (p-dbRDAs) on the variables that were identified as significant in the full db-RDA.

Differentially methylated regions and gene ontology

We identified differentially methylated regions with functional biological correlates by performing beta-regressions on windows over CpG islands and gene bodies for all 95 individuals with percent methylation as the response variable and population as the explanatory variable. Beta regressions are appropriate for proportion or percentage data[55], and we set an alpha threshold at conservative levels seen in similar studies[34] (p-value < 0.001). Overall differences in percent methylation were calculated, and genes were identified as either hypermethylated or hypomethylated based on their relative degree of methylation compared to other populations. Direct overlap between our differentially methylated regions and the felcat9.0 gene annotations were extracted using Seqmonk[51]. We then identified functional associations by searching UniProt (https://www.uniprot.org) by gene name against the database of genes in the domestic cat genome using the search term "organism: *'Felis catus* (Cat) (*Felis silvestris catus*) (9685)'".

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Author Contributions

All authors contributed equally to this work.

Competing Interests

The authors declare no competing interests with this work.

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Table 1. List of differentially methylated regions that have direct overlap with annotated genes. Differentially methylated regions were identified using beta regressions with a p-value < 0.001 and when methylation levels differed by more than 10% between the identified population and the others. Hyper- and hypo-methylation is relative to the other three populations. GO annotated functions were retrieved from UniProt (www.uniprot.org).

Population	Gene	UniProt ID	P-Value	% Difference	Hyper/Hypo-Methylated	GO Annotated Function
Alaska	ADGRL2	M3XFT6_FELCA	7.58E-07	20.17	Hyper	Carbohydrate binding, G-protein coupled receptor activity
	ANK2	M3WXH8_FELCA	2.41E-05	16.10	Hyper	Spectrin binding, maintenance of cytoskeletal structure
	ATP8A1	M3WM63_FELCA	0.000701	14.99	Hyper	ATP binding, magnesium ion binding
Manitoba	NRG3		0.000216	25.43	Hypo	No Uniprot Annotation
	RWDD1	M3XFU2_FELCA	1.86E-05	17.61	Hyper	Cytoplasmic translation
Newfoundland	CDH18	M3WJ78_FELCA	2.83E-05	21.23	Hypo	Calcium ion binding
	CENPU	M3W3F1_FELCA	0.000895	13.71	Hyper	Embryonic development
	CRISPLD1	M3W2H3_FELCA	0.000337	19.82	Hyper	Face morphogenesis
	DCC	M3WHY3_FELCA	0.000399	37.36	Hyper	Spinal cord ventral commissure morphogenesis
	FAM35A	M3WZ20_FELCA	0.000641	19.62	Hyper	No Uniprot Annotation
	HDAC9	A0A2I2U9G1_FELCA	4.40E-05	39.60	Hyper	Histone deacetylase; transcription regulation; downregulation associated with diminished body mass, adaptive thermogenesis[31]
	LOC101091724		0.000698	26.54	Hypo	lncRNA
	LOC109493917		0.000332	38.44	Hypo	lncRNA
	PBX3	M3WKS0_FELCA	3.21E-05	26.60	Hypo	DNA binding transcription factor activity
	TMOD2	M3X1Q9_FELCA	0.000847	29.43	Hyper	Myofibril assembly, muscle contraction, epithelial cell morphology[56]
	ZEB1	A0A2I2UAU6_FELCA	5.73E-05	37.60	Hyper	DNA-binding, transcription factor, regulation of adipose tissue mass[57]

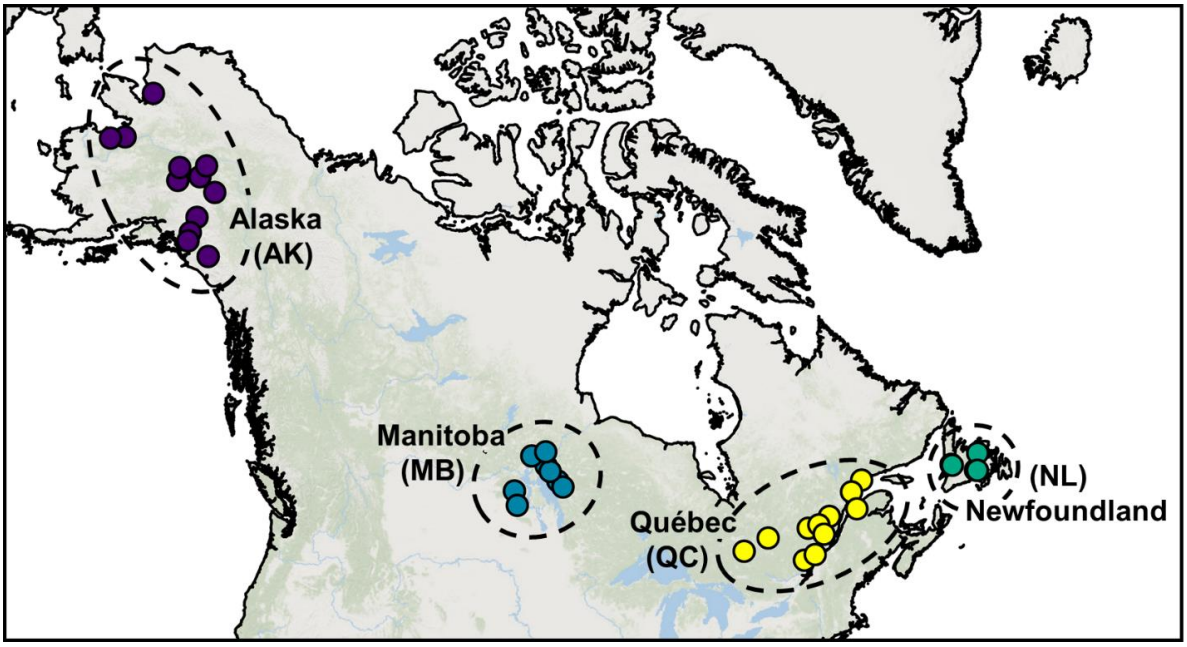

Figure 1. Distribution of 95 Canada lynx (*Lynx canadensis*) samples across North America, used for high-throughput bisulfite sequencing. All four populations are delineated by colour and include 24 individuals, except Alaska (n = 23).

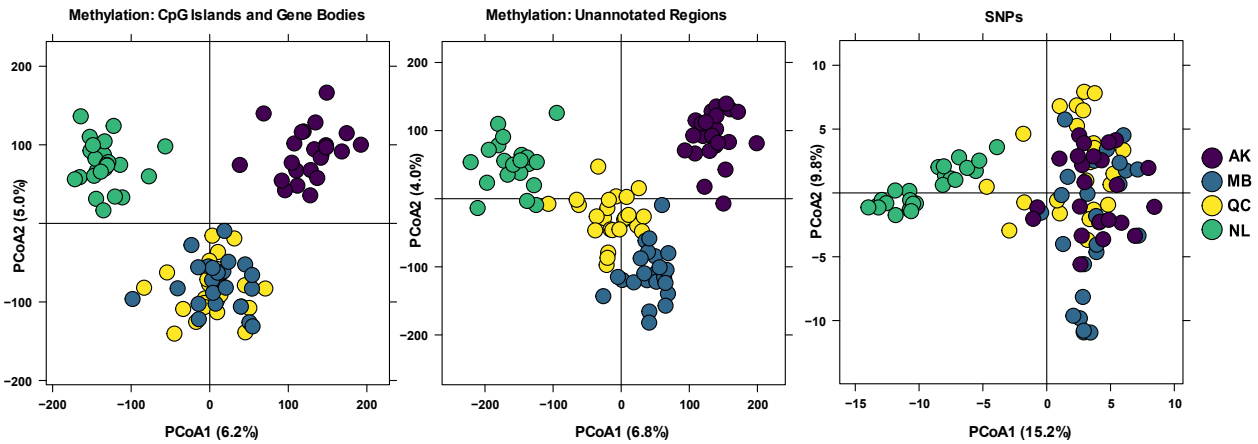

Figure 2. Principal coordinates analysis (PCoA) plots of variation across three molecular marker datasets, with individuals as single circles and populations delineated by colour. All molecular data was summarized with a pair-wise Euclidean dissimilarity matrix. Methylation was summarized with 5,000-bp running windows over CpG islands and gene bodies (n = 329) and over unannotated regions (n = 376). SNP variants were called from bisulfite converted reads and reflect unstructured mainland populations (n = 496).

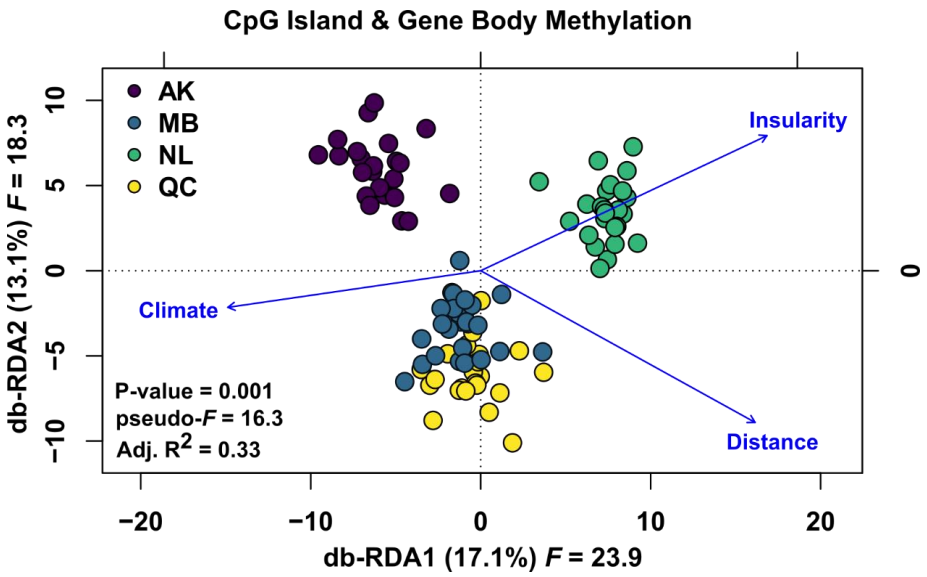

Figure 3. Distance-based redundancy analysis (db-RDA) on DNA methylation data over CpG islands and gene bodies, with population delineated by colour. The axes of a principal coordinates analysis (PCoA) were used a response variable to determine biogeographical relationships. The explanatory variables included a distance variable (the first axis of a PCoA on latitude and longitude); insularity (a binary variable distinguishing the Newfoundland island population); and climate (the first axis of a PCA summarizing winter precipitation, annual temperature ranges, and coldest minimum temperature).

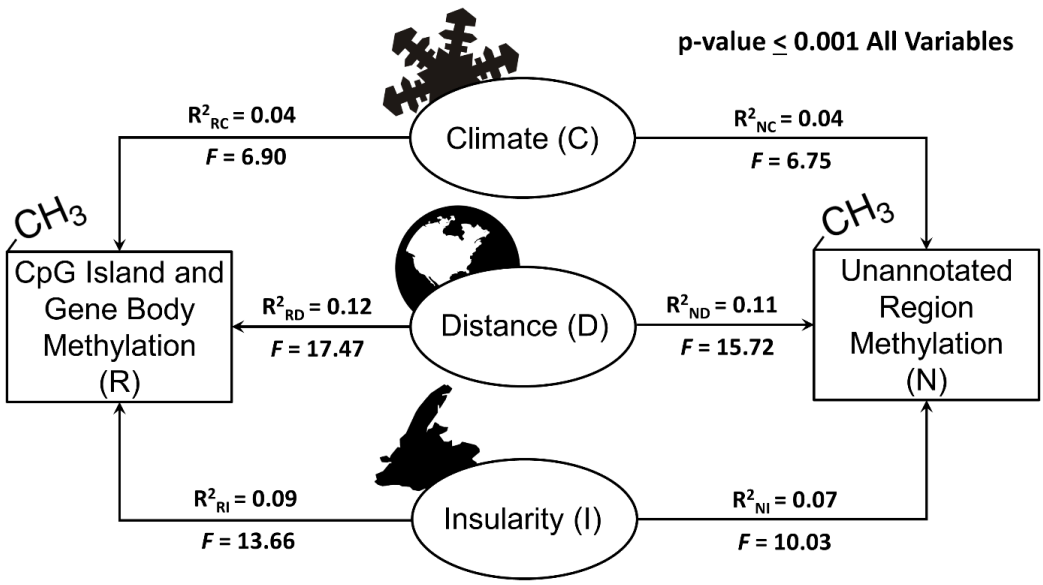

Figure 4. Visual depiction of partial distance-based redundancy analyses (p-db-RDAs). The effect sizes indicate the independent explanatory effects of each variable on explaining methylation patterns, subtracted from the effect of any other variable. The effect size is adjusted R^2, (adj. R^2) and the test-statistic is a pseudo-***F*** generated using QR decomposition within *vegan*.