Comparative analysis examining patterns of genomic differentiation across multiple

episodes of population divergence in birds

Kira E. Delmore[1*], Juan Lugo[1], Benjamin M. Van Doren[2], Max Lundberg[3], Staffan Bensch[3],

Darren E. Irwin[4], Miriam Liedvogel[1]

[1] Max Planck Institute for Evolutionary Biology, Behavioural Genomics, 24306 Plön,

Germany.

[2] Edward Grey Institute, Department of Zoology, University of Oxford, Oxford, OX1 3PS,

United Kingdom.

[3] Lund University, Department of Biology, Ecology Building, 223 62 Lund, Sweden.

[4] Biodiversity Research Center, University of British Columbia, Vancouver, British

Columbia, V6T 1Z4, Canada.

* Corresponding author, delmore@evolbio.mpg.de, +49 (4522) 763 – 268

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Heterogeneous patterns of genomic differentiation are commonly documented between

closely related populations and there is considerable interest in identifying factors that

contribute to their formation. These factors could include genomic features (e.g., areas of low

recombination) that promote processes like linked selection (positive or purifying selection

that affects linked neutral sites) at specific genomic regions. Examinations of repeatable

patterns of differentiation across population pairs can provide insight into the role of these

factors. Birds are well suited for this work, as genome structure is conserved across this

group. Accordingly, we re-estimated relative (F_{ST}) and absolute (d_{XY}) differentiation between

eight sister pairs of birds that span a broad taxonomic range using a common pipeline. Across

pairs, there were modest but significant correlations in window-based estimates of

differentiation (up to 3% of variation explained for F_{ST} and 26% for d_{XY}), supporting a role for

processes at conserved genomic features in generating heterogeneous patterns of

differentiation. This suggestion was reinforced by linear models identifying several genomic

features (e.g., gene densities) as significant predictors of F_{ST} and d_{XY} repeatability. F_{ST}

repeatability was higher among pairs that were further along the speciation continuum (i.e.,

more reproductively isolated), suggesting that early stages of speciation may be dominated by

positive selection that is different between pairs and replaced by processes acting according to

shared genomic features as speciation proceeds.

INTRODUCTION

The integration of genomic data into research on population differentiation and speciation has led to the observation that genomic differentiation between closely related populations is often highly variable across the genome, with areas of elevated differentiation interspersed with areas of low differentiation (e.g., Nadeau et al. 2013; Renaut et al. 2013; Han et al. 2017; Vijay et al. 2017). One of the main conclusions from this observation is that speciation can proceed through a few focal changes and does not require divergence across the entire genome. This conclusion conforms to the genic view of speciation proposed by Wu (2001), but there is still considerable controversy concerning the factors that generate variation in estimates of genomic differentiation. This controversy has led to the development and extensive evaluation of two models.

The first model is termed divergence-with-gene-flow and invokes both selection and gene flow to explain heterogeneous patterns of differentiation. Specifically, this model holds that divergent selection at loci involved in population differentiation protects some regions of the genome from gene flow, elevating an otherwise homogenized landscape of differentiation (Nosil et al. 2009; Nosil and Feder 2012). The second model proposes that selection alone can generate variation in differentiation by accelerating lineage sorting at some regions of the genome. In other words, genomic regions that do not show elevated differentiation simply continue to share ancestral polymorphism (Noor and Bennett 2009; Turner and Hahn 2010; Cruickshank and Hahn 2014). We refer to this model as selection-in-allopatry and note that there are variants on this model related to when selection acts (Cruickshank and Hahn 2014; Delmore et al. 2015; Irwin et al. 2016).

One common feature of both the divergence-with-gene-flow and selection-in-allopatry

models is that features of the local genomic landscape should contribute to variation in

differentiation. For example, genomic regions with lower rates of recombination, higher rates

of mutation and elevated gene densities can promote linked selection, defined as any form of

selection that reduces variation at nearby neutral sites (Charlesworth et al. 1993; Lohmueller

et al. 2011; Charlesworth 2012; Cutter and Payseur 2013; Enard et al. 2014). Linked selection

can be positive, acting on new or existing mutations (genetic hitchhiking, Maynard Smith and

Haigh 1974) or purifying, removing deleterious mutations from the population (background

selection, Charlesworth et al. 1993). Measures of differentiation like F_{ST} include a term for

within population variation and can be inflated by the reductions in variation that accompany

linked selection (Charlesworth 1998). Low recombination rates make it difficult for linked

neutral sites to escape the effects of new mutations via recombination. Higher mutation rates

and gene densities provide more targets for selection which is also expected to be stronger in

gene rich regions where mutations are more likely to have deleterious effects.

It was recently suggested that patterns of genomic differentiation will reflect features

of the local genomic landscape more at later stages of speciation, as drift and background

selection at these features will take time to influence differentiation (Burri 2017).

Comparative analyses examining genomic differentiation across multiple population pairs are

ideal for both implicating features of the local genomic landscape in generating genomic

differentiation and examining their temporal effects. For example, if genomic variables are

conserved across pairs, constraints imposed by processes like linked selection in these regions

should generate correlated or repeated patterns of genomic differentiation. Comparative

analyses are beginning to accumulate but are often limited to a closely related group of

species or populations, precluding an evaluation of temporal effects and introducing statistical

non-independence if a limited number of pairs are included (e.g., sticklebacks, Jones et al.

2012; sunflowers, Renaut et al. 2014; guppies, Fraser et al. 2015; songbirds, Irwin et al. 2016;

Van Doren et al. 2017; copepods, Pereira et al. 2016). In addition, working at broader

taxonomic scales may eliminate the role shared selective regimes play in generating

repeatable patterns of differentiation, isolating the effects of genomic constraints.

Here we overcome these limitations using new and archived genomic data to estimate

genomic differentiation between eight pairs of birds that span a broad taxonomic range (the

most recent common ancestor to them all was ~52 MYA, http://www.timetree.org/). We look

for (1) correlated patterns of genomic differentiation across these pairs (referred to as

"repeatability") and (2) an association between repeatability and the location of pairs along

the speciation continuum (i.e., their level of reproductive isolation). We also (3) use linear

models to implicate specific genomic features in generating repeatable patterns of genomic

differentiation; these features include proxies for both recombination and mutation rates, gene

density, chromosome size and proximity to chromosome ends and centromeres. We

quantified the speciation continuum using hybrid zone width and genetic distance between

pairs. Chromosome size, proximity to chromosome ends and centromeres may influence

genomic differentiation as they have shown associations with recombination rates (Butlin

2005; Smukowski and Noor 2011). We also include linkage disequilibrium (LD) as a

predictor in linear models; if linked selection is generating repeatable patterns, LD should be

higher where repeatability is higher. Birds are well suited for this work as a considerable

amount of information is known about speciation in this group (Price 2008) and genomic

features are highly conserved across this group; birds have stable chromosome numbers, low

rates of interchromosomal rearrangements, high synteny and similar recombination

landscapes (Dawson et al. 2007; Griffin et al. 2007; Backström et al. 2008; Stapley et al.

2008; Ellegren 2010; Kawakami et al. 2014; Zhang et al. 2014; Kawakami et al. 2017).

Thus far we have only discussed how the local genomic landscape can affect F_{ST}, a

relative measure of differentiation that is inflated by reductions in within population variation.

Many studies are beginning to include d_{XY} in their analyses. d_{XY} is an absolute measure of

differentiation that does not include a term for within population variation. Under the

divergence-with-gene-flow model of speciation, processes like linked selection at genomic

features should elevate d_{XY} beyond average, background levels of absolute differentiation.

Under the selection-in-allopatry model of speciation, linked selection should have no effect

on d_{XY} or reduce it beyond background levels (Nachman and Payseur 2012). The latter

reductions could occur in response to recurrent selection in ancestral populations that reduces

variation over lineage splits and/or selective sweeps of globally adaptive alleles (e.g.,

Delmore et al. 2015; Irwin et al. 2016). Given increasing interest in d_{XY} and its potential to

reflect the local genomic landscape, we will include it in our analyses as well. All of the

population pairs included in the present study occur in the temperate region where they have

likely experience periods of allopatry with glacial expansions (Hewitt 2000). Accordingly, in

analyses for objective 3 where we identify specific regions that show repeatable patterns we

will focus on those at the bottom of the d_{XY} distribution; d_{XY} should reflect the amount of

sequence divergence that has been acquired since populations split but linked selection should

reduce this parameter in some regions when gene flow is restricted between populations.

RESULTS

The eight pairs of birds in our study include two populations of European blackcaps (*Sylvia*

atricapilla), subspecies of greenish warbler (*Phylloscopus trochiloides viridanus* and *P. t.*

plumbeitarsus), subspecies of willow warbler (*Phylloscopus trochilus trochilus* and *P.t.*

acredula), species of stonechat (European *Saxicola rubicola* and Siberian *S. maurus*),

subspecies groups of the Swainson's thrush (coastal *Catharus ustulatus ustulatus* and inland

C. u. swainsoni), species of flycatcher (collared *Ficedula albicollis* and pied *F. hypoleuca*),

species of crow (hooded *Corvus cornix* and carion *C. corone*), and species of wood warbler

(blue- *Vermivora chrysoptera* and golden-winged *V. cyanoptera* warblers; Figure 1). To gain

an overview of the relationship between these pairs, we constructed a phylogeny for the group

using whole-genome sequence data from all autosomal chromosomes (Figure 1). The crow is

the most distantly related species; all the remaining species cluster into two groups. One

group includes the greenish warbler, willow warbler and blackcap while the other includes the

flycatcher, stonechat, thrush and blue/golden-winged warblers. Disregarding sister-pair

relationships, the most closely related species are flycatchers and stonechats, and greenish and

willow warblers. This topology is what we expected based on previous phylogenetic studies

(e.g., Jetz et al. 2012, birdtree.org).

Repeatability in patterns of genomic differentiation

To estimate repeatability in patterns of genomic differentiation across pairs we organized

scaffolds from each species' reference into chromosomes using synteny with the flycatcher

and estimated F_{ST} and d_{XY} between populations in each pair using the same 100 kb windows

(Figure 1). An initial comparison across pairs suggests that patterns may only be modestly

consistent but stronger when considering d_{XY}. We evaluated this observation by correlating

windowed estimates of F_{ST} and d_{XY} across pairs. In accordance with our observation,

correlation coefficients varied from -0.02 to 0.18 for F_{ST} and 0.04 to 0.51 for d_{XY} (Table 1).

Squaring the highest coefficients for F_{ST} and d_{XY}, these results suggest that up to 3 and 26% of

the variation can be explained by correlations of F_{ST} and d_{XY} between pairs.

We used a second method to quantify repeatability between pairs based on the overlap

of outlier windows. We identified outlier windows for each pair as those in the top 5

percentile of the F_{ST} distribution and bottom 5 percentile of the d_{XY} distribution and compared

the number of outlier windows that were shared (or overlapped) across pairs to the expected

number based on the hypergeometric distribution (see Methods). Similar to results from

correlations, estimates of overlap were higher and more significant for d_{XY} (Table S3a). This

was also the case when we combined strings of outlier windows into peaks, acknowledging

the fact outlier windows may not be independent of one another (Table S3b).

Association between repeatability and the speciation continuum

We looked for an association between repeatability and the speciation continuum using three

different measures for the speciation continuum: hybrid zone width and genetic distance

based on *cytb* sequences and all autosomal sequences. Starting with hybrid zone width, we

obtained estimates for each pair from the literature and assumed the more narrow a hybrid

zone is the higher reproductive isolation must be (Barton and Hewitt 1985). Estimates of

hybrid zone width ranged from 0 km for greenish warblers to 600 km for blue/golden-winged

warblers (Table S4). We ranked pairs based on hybrid zone width and constructed a distance

matrix by adding the ranks of pairs being compared (Table S4). We compared this matrix

with the correlation matrices generated using windowed estimates F_{ST} and d_{XY} above. As

predicted, there was a positive relationship between hybrid zone width and the correlation

matrix based on F_{ST} but not d_{XY}; pairs further along the speciation continuum showed higher

repeatability in F_{ST} (Mantel Test, R=0.43, p=0.03) but not d_{XY} (R=-0.20, p=0.80).

Similar to results from hybrid zone width, we documented significant positive

associations between matrices based on genetic distance (*cytb* and autosomal) and

repeatability in F_{ST} but not d_{XY} (Mantel Tests, F_{ST}: *cytb*, R=0.36, p=0.05; autosomal, R = 0.54,

p=0.02; d_{XY}: *cytb*, R=-0.04, p=0.56; autosomal, R=0.12, p=0.34). Note that the associations

we documented between repeatability and all three measures of the speciation continuum

remain significant when controlling for phylogenetic distance (e.g., partial Mantel Tests for

F_{ST} and hybrid zone width, R=0.47, p=0.02; *cytb*, R=0.36, p=0.05; autosomal, R=0.43,

p=0.03) and we documented similar associations when we replaced repeatability estimated by

correlation coefficients (Table 1) with values based on the overlap of outlier windows (Table

S3; e.g., results for F_{ST} and hybrid zone width, R=0.29, p=0.06; *cytb*, R=0.40, p=0.01;

autosomal, R=0.41, p=0.01). This is an important finding, as it suggests the associations we

documented are not related to the fact that there is a greater range of F_{ST} values at later stages

of speciation. Finally, note that we obtained similar results when we ran these analyses using

sliding windows of 20 kb (e.g., results for F_{ST} and hybrid zone width, R=0.67, p=0.01; *cytb*,

R=0.32, p=0.05; autosomal, R=0.49, p=0.03).

Genomic features or processes as predictors of repeatability

The repeated patterns of F_{ST} and d_{XY} we documented above suggest that variation in genome-

wide estimates of differentiation is influenced by conserved features of the local genomic

landscape. We used generalized linear models (GLMs) to evaluate the role specific genomic

features play in generating these patterns. Repeatability was quantified for each window as

the number of pairs it was considered an outlier in (recall outlier status was determined using

the top 5 percentile of the F_{ST} distribution and bottom 5 percentile of the d_{XY} distribution).

Separate GLMs were run for each species pair using seven predictor variables (estimated for

each pair separately): the proportion of GC bases (proxy for recombination rate), synonymous

mutation rate (d_s; proxy for mutation rate), gene density, LD and three variables related to

where windows are located in the genome (micro- or macrochromosomes [chromosome size],

proximity to chromosome ends and centromeres).

Results from these GLMs can be found in Figure 2 (with blackcap as predictor) and

Table S5 (for each case as predictor). GC content, gene density, LD and proximity to both

chromosome ends and centromeres were significant predictors of repeatability in F_{ST} across

all species pairs. Each of these variables were positive predictors of repeatability, except GC

content which was negative. In the case of position, this means that windows near the center

of chromosomes showed higher repeatability. Linkage disequilibrium, proximity to

centromeres and chromosome size were significant predictors of repeatability in d_{XY} across all

species pairs. In the case of chromosome size, this means that windows on

microchromosomes show more consistent patterns. GC content, proximity to chromosome

ends, gene density and d_s were also significant predictors of repeatability in d_{XY} but not for all

species pairs.

Note that while the predictor variables used in these models are species-specific (e.g.,

gene density estimate for each pair separately) the response variable is the same – a summary

variable quantifying repeatability across species pairs. Accordingly, results from these models

are not entirely independent.

DISCUSSION

We studied factors influencing variation in genome-wide estimates of differentiation using

genomic data from population pairs of birds that span a broad taxonomic scale. Our results

support a role for (1) features of the local genomic landscape in influencing differentiation

and (2) suggest that the effects of these features become more apparent later in speciation. We

discuss these findings and important caveats below.

238     Our first objective was to determine if patterns of genomic differentiation were

correlated (or repeated) across populations pairs. Our results suggest that up to 3% of the

variation in F_{ST} and 26% of the variation in d_{XY} can be explained by correlations across pairs.

Shared features of the genomic landscape likely contribute to these correlations. For example,

linked selection (positive or purifying) is promoted by genomic features and reduces within

population variation, inflating F_{ST}. Many of these genomic features are conserved across birds

(Dawson et al. 2007; Griffin et al. 2007; Backström et al. 2008; Stapley et al. 2008; Ellegren

2010; Kawakami et al. 2014; Zhang et al. 2014; Kawakami et al. 2017) and likely generated

the repeatable patterns we observed. In support of this suggestion, recombination rates

(approximated by GC content) and gene densities, two genomic features that are preserved

across birds and promote linked selection were consistent predictors of repeatability in F_{ST}.

Genetic drift may also contribute to the correlations we documented. For example, drift in low

recombination regions can cause large genomic regions to show consistently high or low F_{ST}.

Nevertheless, drift is generally expected to reduce genetic diversity genome-wide; it may play

a localized effect if (for example) linked selection reduces N_e in areas of low recombination

but this scenario is not independent of selection (reviewed in Charlesworth 2009). Note that

the amount of variation explained by correlations across pairs is not as high as other studies

(e.g., 49-77% of the variation in F_{ST} explained by correlations across subspecies pairs of

greenish warblers in Irwin et al. 2016). Nevertheless, most of these studies focus on pairs that

are much more closely related than those in the present study, such that pairs share more

genomic features and are subject to similar selective forces.

260   Our second objective was to determine if there was a positive association between

261 repeatability and the location of pairs along the speciation continuum. We measured the

262 speciation continuum using hybrid zone width and genetic distance and found that pairs with

263 narrower hybrid zones and greater genetic distances exhibited more similar patterns of F_{ST}.

264 The latent effects of drift and background selection may explain this pattern. Specifically,

265 when population divergence begins, allele frequencies will be roughly equal and F_{ST} will be

266 close to zero. Drift and selection will start acting on standing genetic variation and any new

267 mutations that arise. The effects of drift and background selection may take time to

268 accumulate. Accordingly, positive selection may be the primary force affecting differentiation

269 early in speciation (Burri 2017). If the selective context of speciation is different for the pairs

270 under study, this should lead to less repeatable (or correlated) patterns of differentiation. As

271 speciation proceeds, the effects of drift and background selection will become more

272 pronounced and result in the landscape of differentiation reflecting genomic features that

273 promote these processes (along with positive selection and genetic hitchhiking) more directly

274 (Burri 2017). Note that the beginning stages of speciation may be less repeatable even without

275 different selective pressures. For example, there may be more than one way to respond to

276 selection and the chance positive selection affects the same genomic region may be low. In

277 addition, beneficial mutations are rare (Eyre-Walker and Keightley 2007); during the time it

278 takes for positive selection to act, the regions where differentiation becomes elevated in

279 response to drift and background selection may be unpredictable (Burri 2017).

281   Thus far we have focused mainly on results for F_{ST}; results for d_{XY} require careful

282 explanation. Concerning the repeatable patterns we documented (first objective, up to 26% of

283 the variation in d_{XY} explained by correlations across pairs), at the outset we argued that

284 speciation in the pairs we studied would have been punctuated with periods of allopatry as all

pairs occur in the temperate region where glacial advances would have isolated populations in

different refugia (Hewitt 2000). Under this scenario (i.e., without gene flow), d_{XY} should

reflect the amount of sequence divergence that has been acquired since populations split and

linked selection should have no effect on d_{XY} or reduce it (e.g., if recurrent selection in

ancestral populations removes variation from populations prior to their split; Nachman and

Payseur 2012; Cruickshank and Hahn 2014). In support of this finding, several genomic

features including gene densities and chromosome size predicted repeatable patterns at the

bottom of the d_{XY} distribution. Nevertheless, it is important to note that linked selection can

also elevate d_{XY}, especially during periods of secondary contact where gene flow would have

occurred and thus some of the repeatable patterns we documented may also be related to

elevated d_{XY} (Nachman and Payseur 2012).

297   Continuing with d_{XY} repeatability (i.e., results for the first objective), correlation

coefficients were higher for d_{XY} than F_{ST}, with the highest correlation coefficient for d_{XY} being

more than twice that for F_{ST} (0.18 vs. 0.51). This finding could be related to the fact that d_{XY}

reflects processes that have accumulated over multiple speciation events (see below for

additional explanation) while F_{ST} mainly reflects process in extant populations. Accordingly,

if population pairs are sampled too early in speciation, F_{ST} may not reflect local genomic

features yet (Burri 2017). This suggestion follows from the argument described above about

the latent effects of drift and background selection. Nevertheless, additional explanations for

increased d_{XY} repeatability are also possible. For example, d_{XY} shows a strong relationship

with mutation rates (Geneva et al. 2015; Rosenzweig et al. 2016). Accordingly, much of the

pattern we documented may be related solely to variation in mutation rates. It is also

important to note that d_{XY} is estimated using far more sites than F_{ST} (variant and invarant vs.

just variant for F_{ST}). Accordingly, these estimates may be more precise, leading to stronger

correlation coefficients.

Finally, while we found a correlation between the speciation continuum and

repeatability in F_{ST} (second objective) we did not document this association for d_{XY}. Again,

this finding may be related to the fact that d_{XY} reflects processes that have accumulated over

multiple speciation events while F_{ST} mainly reflects process in extant populations, including

speciation. For example, if the recombination landscape has remained the same for millions of

years, recurrent linked selection in areas of low recombination has likely been reducing

variation over the same time period and these reductions will be passed down over speciation

events (Burri 2017). Under this scenario, it will not matter what stage of differentiation the

population pairs under study are at, these reductions will be reflected in estimates of d_{XY}. As

we have already discussed, there are situations where d_{XY} will reflect processes in extant

populations (especially if gene flow is occurring) but the underlying effect of ancestral

diversity appears to override any effect these processes have on d_{XY} repeatability and the

speciation continuum.

We used a comparative analysis to provide insight into how heterogeneity in both

relative and absolute differentiation are generated and change during the process of

speciation, implicating processes at conserved genomic features in generating variation in

both measures of differentiation and providing evidence that these processes have a greater

effect on relative estimates of genomic differentiation later in speciation. By working at such

a broad taxonomic scale we were able to reduce the effect shared selective regimes may play

in generating repeated patterns of differentiation. By including population pairs with good

information on reproductive isolation, we were able to provide some of the first empirical

evidence for the latent effects of drift and background selection on relative differentiation and

highlight the importance of the selective context (i.e., positive selection and genetic

hitchhiking) early in speciation. Our results support the general sentiment (e.g., Ravinet et al.

2016) that caution must be used when interpreting patterns of differentiation, as processes

other than positive selection can influence differentiation. In addition, there is increasing

interest in applying additional measures of differentiation beyond F_{ST} to speciation genomics

but as highlighted by the caveats we discuss for d_{XY}, careful consideration must be used when

applying them to this topic.

METHODS

Study Species and Datasets

We searched the Sequence Read Archive (https://www.ncbi.nlm.nih.gov/sra) and European

Nucleotide Archive (http://www.ebi.ac.uk/ena) for genomic data collected from birds. We

limited our search to species for which a draft reference genome had been assembled for the

target species or one that was closely related. This search resulted in the inclusion of eight

pairs (Table S1). The only pair we did not have a reference genome for was the *Vermivora*

warblers but a reference for the closely related yellow-rumped warblers (*Setophaga coronata*)

is available and was used in the original publication for these data (Toews et al. 2016). All

pairs are from the order Passeriformes (perching birds or songbirds) and breed in temperate

regions (Figure 1).

Generating consensus reference genomes

The reference genomes we acquired were all assembled into scaffolds, except the collared

flycatcher's genome, which was organized into chromosomes based on linkage map for the

species and synteny with zebra finch (Ellegren et al. 2012). Accordingly, we used this

genome to ensure all windows compared across species were orthologous. To maintain

chromosomal synteny, we aligned the scaffolds of each genome individually against the

flycatcher genome with SatsumaSynteny (default parameters; Grabherr et al. 2010). We then

used bash scripts to parse the output, obtaining information on the order and orientation of

query scaffolds and conducted a final alignment with the LASTZ plugin in Geneious (Harris

2007; Kearse et al. 2012). We merged these scaffolds into pseudochromosomes by calling the

query base where alignments occurred and Ns in the presence of a gap. Details on consensus

genome coverage can be found in Table S2.

368   Constructing phylogenetic network

We used ANGSD (Korneliussen et al. 2014) to obtain consensus fasta sequences for

populations from each species pair (-doFasta 2 -doCounts 1 -minQ 20 -setMinDepth 10) and

IQ-TREE (Nguyen et al. 2016) to generate a distance matrix based on these sequences. We

used the resulting distance matrix to construct a phylogenetic tree using the UPGMA

clustering method in PHYLUCE (neighbor,

http://evolution.genetics.washington.edu/phylip/doc/neighbor.html).

376   Estimating differentiation

We focused on SNPs for the present study and used a common reference-based

bioinformatics pipeline to call them. Details can be found in Delmore et al. (2015) and

Delmore et al. (2016). Briefly, we trimmed reads with trimmomatic (TRAILING:3

SLIDINGWINDOW:4:10 MINLEN:30) and aligned them to consensus genomes using bwa

mem (Li and Durbin 2009) using default settings. We then used GATK (McKenna et al. 2010)

and picardtools (http://broadinstitute.github.io/picard) to identify and realign reads around

indels (*RealignerTargetCreator*, *IndelRealigner*, default settings) and removed duplicates

(*MarkDuplicates*, default settings) for all datasets except greenish warbler which consisted of

GBS data.

We used two estimates of differentiation in our study: F_{ST} and d_{XY}. We estimated F_{ST}

for datasets comprised of individuals using ANGSD, estimating site frequency spectrums for

each population separately (-dosaf 1, -gl 1, -remove_bads, -unique_only, -minMapQ 20, -

minQ 20, -only_proper_pairs 1, -trim 0) and using these to obtain joint frequencies spectrums

for population pairs. These joint frequency spectrums were then used as priors for allele

frequencies at each site to estimate F_{ST}. For datasets comprised of pools we estimated F_{ST}

using Popoolation2 (Kofler et al. 2011; -min-coverage 30 for Swainson's thrushes and 10 for

stonechats, -min-count 3, -minq 20). We summarized F_{ST} into windows of 100 kb and limited

analyses to windows with data from all pairs. We excluded the Z chromosome from all

analyses as some of the pairs included females where systematic biases related to coverage

could affect estimates of differentiation.

We estimated d_{XY} for datasets comprised of individuals using ANGSD as well. First,

we estimated allele frequencies at each SNP for both populations of each pair combined -

doMajorMinor 4, -doMaf 2, -gl 1, -doCounts 1, -remove_bads, -unique_only, -minMapQ 20, -

minQ 20, -only_proper_pairs 1, -trim 0, -SNP_pval 1e-6). We then reran the program by

population using only the SNPs that passed the previous step, to ensure SNPs fixed in one

population were not lost. Once we had these allele frequencies, we estimate d_{XY} at each SNP

using a script provided with ANGSD (https://github.com/mfumagalli/ngsPopGen/

/scripts/calcDxy.R) and as (p1*(1-p2))+(p2*(1-p1)) where p is the allele frequency of a given

allele in populations 1 and 2, respectively and averaged these values in the same 100 kb

windows used for F_{ST}. Estimates of d_{XY} by SNP have to be normalized by the number of sites

(variant and invariant) in a window. We obtained these values using ANGSD to estimate read

depth at all sites (-doCounts 1, -dumpCounts 1, -remove_bads, -unique_only, -minMapQ 20, -

minQ 20, -only_proper_pairs 1, -trim 0) and excluded sites with coverage less than three

times the sample size and more than three times the average coverage to ensure roughly three

reads per individual and exclude sites that may have mapping problems resulting from copy

number variants. Analyses were limited to windows with data from all pairs and windows

with more than 5000 callable sites, as d_{XY} can be highly variable with small sample sizes and

coverage (e.g., Clarkson et al. 2014). This filter precluded the use of greenish warblers in

analyses of d_{XY} as data for this pair were derived from reduce-representation sequencing and

did not have high coverage in windows of 100 kb. This was not a problem for the original

publication (Irwin et al. 2016) as windows were defined by SNPs rather than base pairs.

For stonechats and thrushes, for which we used pooled sequencing data, we calculated

d_{XY} with a custom script. We excluded sites with coverage below 10 for stonechats and below

30 for thrushes. We estimated d_{XY} by multiplying allele frequencies for each base as above

and averaging across sufficiently covered bases in each window.

Estimating repeatability in patterns of genomic differentiation

We estimated overall repeatability between pairs by correlating windowed-estimates of

differentiation across pairs. We also estimated repeatability using information on outlier

status and overlap. Specifically, we identified outlier windows for each species pairs as those

above the 5% quantile for F_{ST} and below the 5% quantile for d_{XY}. For each comparison across

pairs (e.g., flycatcher to stonechat, flycatcher to greenish warbler, etc.), we counted the

number of outlier windows that were shared (or overlapped) and compared this to the

expected number of overlapping windows using the hypergeometric distribution, assuming

that each window had an equal probability of being considered an outlier. We used these

values (observed and expected) to calculate z scores for each comparison and calculated one-

sided p-values (i.e., the probability of obtaining an overlap value as extreme or more extreme

than our observed value). Z scores are effect sizes that correspond to the number of standard

deviations above the average expectation in each comparison, allowing for direct comparison

across studies. Note that it is also possible that the outlier windows we identified are not

independent of one another. Accordingly, we modified our overlap approach by combining

outlier windows into peaks if they occurred next to one another and using the number of

peaks as our estimate of overlap. We used a permutation test to quantify the significance of

these values, holding the number and size of outlier regions constant while randomly

permuting their location 1000 times and calculating one-sided p-values again (Van Doren et

al. 2017).

Placing pairs along the speciation continuum

We used three methods to place pairs along the speciation continuum (i.e., to quantify the

level of reproductive isolation), starting with the width of hybrid zones, which we obtained

from the literature. The more narrow a zone the higher the reproductive isolation (Barton and

Hewitt 1985; Moore and Dolbeer 1989; Paradis et al. 1998). If hybridization is extremely rare

(e.g., with the greenish warblers), we set the width as zero. Note the use of hybrid zone width

as a measure for reproductive isolation assumes all hybrid zones are at an equilibrium

between selection and dispersal (Barton & Hewitt 1985) and that dispersal distances are

similar across pairs. We also used genetic distance within pairs, which we obtained by

aligning *ctyb* sequences (downloaded from NCBI https://www.ncbi.nlm.nih.gov/) using

MEGA as *p*-distance (the proportion of nucleotide sites that differ between groups) and the

distance matrix generated by IQTREE for autosomal chromosome alignments (see

"Consructing phylogenetic network"). We used Mantel tests to compare distance matrices

quantifying the speciation continuum with distance matrices quantifying repeatability. We

accounted for small sample sizes in these tests by using permutation tests to quantify

significance and the non-parametric Spearman rank correlation coefficient.

Measuring genomic features and processes and their effect on repeatability

We looked at the relationship between repeatability and seven structural features of the

genome: recombination rate, mutation rate, gene density, chromosome size, proximity to

chromosome ends and centromeres and linkage disequilibrium. We estimated these features

for each species and ran separate generalized linear models with repeatability as the response

variable with a Poisson distribution for each species.

We used GC content as a proxy for recombination. Recombination affects the patterns

of local base composition via the unbalanced transmission of 'strong' (GC) over 'weak' (AT)

alleles at double-strand breaks (Mugal et al. 2015). This process is termed GC-biased gene

conversion and direct support was recently presented in birds (Smeds et al. 2016). Positive

correlations between recombination and GC content have also been documented in birds

(Kawakami et al. 2014; Burri et al. 2015). Synonymous mutations occur in the exon of genes

but have no effect on the sequence of amino acids. The use of d_s for mutation rate analysis

assumes these sites do not experience selection (Eyre-Walker and Keightley 1999). We used a

phylogenetic framework to obtain these estimates; details can be found in the Supplementary

Methods. Briefly, we annotated each consensus genome with MAKER and identified

potential homologues for high quality transcripts (AED < 0.05) using a Blastn search against

all transcripts from the flycatcher (flycatcher was searched against zebra finch). We aligned

codons from each pair of sequences using PRANK (http://wasabiapp.org/software/prank) and

calculated d_N/d_s with PAML v4.8. All d_N/d_s calculations were performed pairwise, comparing

all the species with the flycatcher and this in turn, compared to zebra finch. Estimates of d_s

were extracted for GLMs. We used PLINK 1.9 (Chang et al. 2015) to estimate linkage

disequilibrium for one population from each pair (the same population for which we had a

reference genome), as the squared correlation coefficient (r^2) between pairs of SNPs. SNPs

were output from ANGSD using the same filters described above for F_{ST} and d_{XY} and

including an additional filter for minor allele frequency, requiring SNPs have minor allele

frequencies greater than 0.05. PLINK was run with the command line with the command line

'--ld-window 100 --ld-window-kb 100 --ld-window-r2 0' to limit the analyses to SNPs with

fewer than 100 variants between them and no more than 100 kilobases apart and report pairs

with r^2 values below 0.2 as well. We determined the midpoints for all SNP pairs, binned them

into the same 100 kb windows used for F_{ST} and d_{XY} and calculated average values for each

window.

Avian genomes are composed of micro- and macrochromosomes. We considered

microchromosomes those that are less than 20 Mb (Ellegren 2013) and macrochromosomes

those that are greater than 40 Mb. We identified the position of each window along the

chromosome by dividing chromosomes in half and generating a variable that increased by 1

from each end to the middle of a chromosome. We standardized this measure by dividing

these values by half the number of windows on each chromosome. We inferred the location of

centromeres using methods employed by Ellegren et al. (2012) and Delmore et al. (2015).

Specifically, we identified FISH probes from Warren *et al.* (2010) on either side of

centromeres in the zebra finch genome and used NCBI's blastn (Altschul et al. 1990) to find

their location in our genome. We considered sequences between FISH probes as "centromeric

regions" and note this method only gives us a rough approximation for the location of

centromeres.

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AUTHOR CONTRIBUTIONS

KD and MLi conceived and designed the study, all authors contributed data. KD conducted

all analyses excluding the estimation of d_{XY} for pooled datasets and repeatability using peaked

overlap values (BV). JL helped with the construction of consensus genomes and estimates of

d_s and MLu with the estimation of d_{XY} for individual datasets. KD wrote the manuscript with

comments from all authors.

DATA ACCESSIBILITY

Accession numbers for all genomic data used in this paper can be found in Table S1.

REFERENCES

Altschul, S. F., W. Gish, W. Miller, E. W. Myers, and D. J. Lipman. 1990. Basic local

alignment search tool. J. Mol. Biol. 215:403–410.

Backström, N., N. Karaiskou, E. H. Leder, L. Gustafsson, C. R. Primmer, A. Qvarnström, and

H. Ellegren. 2008. A gene-based genetic linkage map of the collared flycatcher

(*Ficedula albicollis*) reveals extensive synteny and gene-order conservation during

100 million years of avian evolution. Genetics 179:1479–1495.

Barton, N. H., and G. M. Hewitt. 1985. Analysis of hybrid zones. Annu. Rev. Ecol. Syst.

16:113–148.

Burri, R. 2017. Interpreting differentiation landscapes in the light of long-term linked

selection. Evol. Lett. 1:118–131.

Burri, R., A. Nater, T. Kawakami, C. F. Mugal, P. I. Olason, L. Smeds, A. Suh, L. Dutoit, S.

Bureš, L. Z. Garamszegi, S. Hogner, J. Moreno, A. Qvarnström, M. Ružić, S.-A.

Sæther, G.-P. Sætre, J. Török, and H. Ellegren. 2015. Linked selection and

recombination rate variation drive the evolution of the genomic landscape of

differentiation across the speciation continuum of *Ficedula flycatchers*. Genome Res.

25:1656–1665.

Butlin, R. K. 2005. Recombination and speciation. Mol. Ecol. 14:2621–2635.

Charlesworth, B. 2009. Effective population size and patterns of molecular evolution and

variation. Nat. Rev. Genet. 10:195–205.

Charlesworth, B. 1998. Measures of divergence between populations and the effect of forces

that reduce variability. Mol. Biol. Evol. 15:538–543.

Charlesworth, B. 2012. The role of background selection in shaping patterns of molecular

evolution and variation: evidence from variability on the *Drosophila* X chromosome.

Genetics 191:233–246.

Charlesworth, B., M. T. Morgan, and D. Charlesworth. 1993. The effect of deleterious

mutations on neutral molecular variation. Genetics 134:1289–1303.

Clarkson, C. S., D. Weetman, J. Essandoh, A. E. Yawson, G. Maslen, M. Manske, S. G.

Field, M. Webster, T. Antão, B. MacInnis, D. Kwiatkowski, and M. J. Donnelly.

2014. Adaptive introgression between *Anopheles* sibling species eliminates a major

genomic island but not reproductive isolation. Nat. Commun. 5:5248.

Cruickshank, T. E., and M. W. Hahn. 2014. Reanalysis suggests that genomic islands of

speciation are due to reduced diversity, not reduced gene flow. Mol. Ecol. 23:3133–

3157.

Cutter, A. D., and B. A. Payseur. 2013. Genomic signatures of selection at linked sites:

unifying the disparity among species. Nat. Rev. Genet. 14:262–274.

Dawson, D. A., M. \AAkesson, T. Burke, J. M. Pemberton, J. Slate, and B. Hansson. 2007.

Gene order and recombination rate in homologous chromosome regions of the chicken

and a passerine bird. Mol. Biol. Evol. 24:1537–1552.

Delmore, K. E., S. Hübner, N. C. Kane, R. Schuster, R. L. Andrew, F. Câmara, R. Guigó, and

D. E. Irwin. 2015. Genomic analysis of a migratory divide reveals candidate genes for

migration and implicates selective sweeps in generating islands of differentiation.

Mol. Ecol. 24:1873–1888.

Delmore, K. E., D. P. L. Toews, R. R. Germain, G. L. Owens, and D. E. Irwin. 2016. The

genetics of seasonal migration and plumage color. Curr. Biol. 26:2167–2173.

Ellegren, H. 2010. Evolutionary stasis: the stable chromosomes of birds. Trends Ecol. Evol.

25:283–291.

Ellegren, H. 2013. The evolutionary genomics of birds. Annu. Rev. Ecol. Evol. Syst. 44:239–

259.

Ellegren, H., L. Smeds, R. Burri, P. I. Olason, N. Backström, T. Kawakami, A. Künstner, H.

Mäkinen, K. Nadachowska-Brzyska, A. Qvarnström, S. Uebbing, and J. B. W. Wolf.

2012. The genomic landscape of species divergence in *Ficedula flycatchers*. Nature

491:756–760.

Enard, D., P. W. Messer, and D. A. Petrov. 2014. Genome-wide signals of positive selection

in human evolution. Genome Res. 24:885–895.

581 Eyre-Walker, A., and P. D. Keightley. 1999. High genomic deleterious mutation rates in

582    hominids. Nature 397:344–347.

583 Eyre-Walker, A., and P. D. Keightley. 2007. The distribution of fitness effects of new

584    mutations. Nat. Rev. Genet. 8:610–618.

585 Fraser, B. A., A. Künstner, D. N. Reznick, C. Dreyer, and D. Weigel. 2015. Population

586    genomics of natural and experimental populations of guppies (*Poecilia reticulata*).

587    Mol. Ecol. 24:389–408.

588 Geneva, A. J., C. A. Muirhead, S. B. Kingan, and D. Garrigan. 2015. A new method to scan

589    genomes for introgression in a secondary contact model. PloS One 10:e0118621.

590 Grabherr, M. G., P. Russell, M. Meyer, E. Mauceli, J. Alföldi, F. Di Palma, and K. Lindblad-

591    Toh. 2010. Genome-wide synteny through highly sensitive sequence alignment:

592    Satsuma. Bioinformatics 26:1145–1151.

593 Griffin, D. K., L. B. W. Robertson, H. G. Tempest, and B. M. Skinner. 2007. The evolution of

594    the avian genome as revealed by comparative molecular cytogenetics. Cytogenet.

595    Genome Res. 117:64–77.

596 Han, F., S. Lamichhaney, B. R. Grant, P. R. Grant, L. Andersson, and M. T. Webster. 2017.

597    Gene flow, ancient polymorphism, and ecological adaptation shape the genomic

598    landscape of divergence among Darwin's finches. Genome Res. 27:1004–1015.

599 Harris, R. S. 2007. Improved pairwise alignment of genomic DNA. Pennsylvania State

600    University.

601 Hewitt, G. 2000. The genetic legacy of the Quaternary ice ages. Nature 405:907–913.

602 Irwin, D. E., M. Alcaide, K. E. Delmore, J. H. Irwin, and G. L. Owens. 2016. Recurrent

603    selection explains parallel evolution of genomic regions of high relative but low

604    absolute differentiation in a ring species. Mol. Ecol. 25:4488–4507.

Jetz, W., G. H. Thomas, J. B. Joy, K. Hartmann, and A. O. Mooers. 2012. The global

diversity of birds in space and time. Nature 491:444–448.

Jones, F. C., M. G. Grabherr, Y. F. Chan, P. Russell, E. Mauceli, J. Johnson, R. Swofford, M.

Pirun, M. C. Zody, and S. White. 2012. The genomic basis of adaptive evolution in

threespine sticklebacks. Nature 484:55–61.

Kawakami, T., C. F. Mugal, A. Suh, A. Nater, R. Burri, L. Smeds, and H. Ellegren. 2017.

Whole-genome patterns of linkage disequilibrium across flycatcher populations clarify

the causes and consequences of fine-scale recombination rate variation in birds. Mol.

Ecol. 26:4158–4172.

Kawakami, T., L. Smeds, N. Backström, A. Husby, A. Qvarnström, C. F. Mugal, P. Olason,

and H. Ellegren. 2014. A high-density linkage map enables a second-generation

collared flycatcher genome assembly and reveals the patterns of avian recombination

rate variation and chromosomal evolution. Mol. Ecol. 23:4035–4058.

Kearse, M., R. Moir, A. Wilson, S. Stones-Havas, M. Cheung, S. Sturrock, S. Buxton, A.

Cooper, S. Markowitz, C. Duran, and others. 2012. Geneious Basic: an integrated and

extendable desktop software platform for the organization and analysis of sequence

data. Bioinformatics 28:1647–1649.

Kofler, R., R. V. Pandey, and C. Schlötterer. 2011. PoPoolation2: identifying differentiation

between populations using sequencing of pooled DNA samples (Pool-Seq).

Bioinformatics 27:3435–3436.

Korneliussen, T. S., A. Albrechtsen, and R. Nielsen. 2014. ANGSD: analysis of next

generation sequencing data. BMC Bioinformatics 15:1.

Li, H., and R. Durbin. 2009. Fast and accurate short read alignment with Burrows–Wheeler

transform. Bioinformatics 25:1754–1760.

Lohmueller, K. E., A. Albrechtsen, Y. Li, S. Y. Kim, T. Korneliussen, N. Vinckenbosch, G.

Tian, E. Huerta-Sanchez, A. F. Feder, N. Grarup, T. Jørgensen, T. Jiang, D. R. Witte,

A. Sandbæk, I. Hellmann, T. Lauritzen, T. Hansen, O. Pedersen, J. Wang, and R.

Nielsen. 2011. Natural selection affects multiple aspects of genetic variation at

putatively neutral sites across the human genome. PLOS Genet. 7:e1002326.

Maynard Smith, J. M., and J. Haigh. 1974. The hitch-hiking effect of a favourable gene.

Genet. Res. 23:23–35.

McKenna, A., M. Hanna, E. Banks, A. Sivachenko, K. Cibulskis, A. Kernytsky, K.

Garimella, D. Altshuler, S. Gabriel, M. Daly, and others. 2010. The genome analysis

toolkit: a MapReduce framework for analyzing next-generation DNA sequencing data.

Genome Res. 20:1297–1303.

Moore, W. S., and R. A. Dolbeer. 1989. The use of banding recovery data to estimate

dispersal rates and gene flow in avian species: case studies in the red-winged

blackbird and common grackle. Condor 242–253.

Mugal, C. F., C. C. Weber, and H. Ellegren. 2015. GC-biased gene conversion links the

recombination landscape and demography to genomic base composition: GC-biased

gene conversion drives genomic base composition across a wide range of species.

BioEssays News Rev. Mol. Cell. Dev. Biol. 37:1317–1326.

Nachman, M. W., and B. A. Payseur. 2012. Recombination rate variation and speciation:

theoretical predictions and empirical results from rabbits and mice. Philos. Trans. R.

Soc. B Biol. Sci. 367:409–421.

Nadeau, N. J., S. H. Martin, K. M. Kozak, C. Salazar, K. K. Dasmahapatra, J. W. Davey, S.

W. Baxter, M. L. Blaxter, J. Mallet, and C. D. Jiggins. 2013. Genome-wide patterns of

divergence and gene flow across a butterfly radiation. Mol. Ecol. 22:814–826.

Noor, M. A., and S. M. Bennett. 2009. Islands of speciation or mirages in the desert?

Examining the role of restricted recombination in maintaining species. Heredity

103:439–444.

Nosil, P., and J. L. Feder. 2012. Genomic divergence during speciation: causes and

consequences. Philos. Trans. R. Soc. B Biol. Sci. 367:332–342.

Nosil, P., D. J. Funk, and D. Ortiz-Barrientos. 2009. Divergent selection and heterogeneous

genomic divergence. Mol. Ecol. 18:375–402.

Paradis, E., S. R. Baillie, W. J. Sutherland, and R. D. Gregory. 1998. Patterns of natal and

breeding dispersal in birds. J. Anim. Ecol. 67:518–536.

Pereira, R. J., F. S. Barreto, N. T. Pierce, M. Carneiro, and R. S. Burton. 2016.

Transcriptome-wide patterns of divergence during allopatric evolution. Mol. Ecol.

25:1478–1493.

Price, T. 2008. Speciation in Birds. Roberts and Company Publishers, Colorado.

Ravinet, M., A. Westram, K. Johannesson, R. Butlin, C. André, and M. Panova. 2016. Shared

and nonshared genomic divergence in parallel ecotypes of *Littorina saxatilis* at a local

scale. Mol. Ecol. 25:287–305.

Renaut, S., C. J. Grassa, S. Yeaman, B. T. Moyers, Z. Lai, N. C. Kane, J. E. Bowers, J. M.

Burke, and L. H. Rieseberg. 2013. Genomic islands of divergence are not affected by

geography of speciation in sunflowers. Nat. Commun. 4:1827.

Renaut, S., G. L. Owens, and L. H. Rieseberg. 2014. Shared selective pressure and local

genomic landscape lead to repeatable patterns of genomic divergence in sunflowers.

Mol. Ecol. 23:311–324.

Rosenzweig, B. K., J. B. Pease, N. J. Besansky, and M. W. Hahn. 2016. Powerful methods for

detecting introgressed regions from population genomic data. Mol. Ecol. 25:2387–

2397.

Smeds, L., C. F. Mugal, A. Qvarnström, and H. Ellegren. 2016. High-resolution mapping of

crossover and non-crossover recombination events by whole-genome re-sequencing of

an avian pedigree. PLOS Genet 12:e1006044.

Smukowski, C. S., and M. A. F. Noor. 2011. Recombination rate variation in closely related

species. Heredity 107:496.

Stapley, J., T. R. Birkhead, T. Burke, and J. Slate. 2008. A linkage map of the zebra finch

Taeniopygia guttata provides new insights into avian genome evolution. Genetics

179:651–667.

Toews, D. P., S. A. Taylor, R. Vallender, A. Brelsford, B. G. Butcher, P. W. Messer, and I. J.

Lovette. 2016. Plumage genes and little else distinguish the genomes of hybridizing

warblers. Curr. Biol. 26:2313–2318.

Van Doren, B.M., Campagna, L., Helm, B., Illera, J.C., Lovette, I.J., Liedvogel, M.

Correlated patterns of genetic diversity across an avian family. Mol. Ecol. 26:3982-

3997.

Turner, T. L., and M. W. Hahn. 2010. Genomic islands of speciation or genomic islands and

speciation? Mol. Ecol. 19:848–850.

Vijay, N., M. Weissensteiner, R. Burri, T. Kawakami, H. Ellegren, and J. B. Wolf. 2017.

Genome-wide patterns of variation in genetic diversity are shared among populations,

species and higher order taxa. Mol. Ecol. 26:4284-4295.

Warren, W. C., D. F. Clayton, H. Ellegren, A. P. Arnold, L. W. Hillier, A. Künstner, S.

Searle, S. White, A. J. Vilella, and S. Fairley. 2010. The genome of a songbird. Nature

464:757–762.

Wu, C.-I. 2001. The genic view of the process of speciation. J. Evol. Biol. 14:851–865.

Zhang, G., E. D. Jarvis, and M. T. P. Gilbert. 2014. A flock of genomes. Science 346:1308–

1309.

Table 1. Repeatability in genomic differentiation across population pairs of birds. Values are correlation coefficients comparing windowed estimates of F_{ST} (below diagonal) and d_{XY} (above diagonal) between each set of population pairs. d_{XY} was not estimated for greenish warblers. For results based on outlier status and overlap values see Table S3.

	Flycatchers	Crows	Willows	Blackcaps	Greenish	Stonechats	Thrushes	Blue/gold
Flycatchers		0.17***	0.21***	0.23***		0.51***	0.11***	0.17***
Crows	0.058***		0.09***	0.14***		0.21***	0.04**	0.22***
Willows	0.020	0.028*		0..29***		0.12***	0.19***	0.24***
Blackcaps	-0.017	0.037**	0.029**			0.18***	0.44***	0.42***
Greenish	0.11***	0.054***	-0.020	0.021				
Stonechats	0.18***	0.099***	0.030**	0.045***	0.14***		0.37***	0.11***
Thrushes	0.084***	0.024**	0.12***	0.0099	0.11***	0.13***		0.21***
Blue/gold	0.0077	0.036*	0.055***	0.052***	0.027*	0.032*	0.099***	

p-values corrected for multiple testing (* 0.05, ** 0.01, *** 0.001)

Figure 1. Population pairs, their (A) geographic ranges (circles as the center of sampling distributions) and (B) phylogenetic relationships (each branch has 100 bootstrapped support). Panel (C) shows windowed (100 kb) estimates of relative (F_{ST}) and absolute (d_{XY}) differentiation across chromosome 19 for all population pairs along with repeatability at the top, measured as the number of pairs each windows as considered an outlier in (top 5 percentile of F_{ST} distribution and bottom 5 percentile of d_{XY} distribution).

Figure 2. Results from GLMs examining the relationship between repeatability and predictor variables related to features of the local genomic landscape. Relationships shown are limited to significant predictor variables and results from blackcaps (results for non-significant predictor

variables and the remaining population pairs and can be found in Table S5). Repeatability is estimated as the number of pairs each window was considered an outlier in (outliers are windows in the top 5 percentile of each species pairs' distribution for F_{ST} [A] and bottom 5 percentile for d_{XY} [B]). Correlation coefficients for full models are 0.17 for F_{ST} and 0.27 for d_{XY}. Parameter estimates are as follows: F_{ST}, GC content -0.20 [±0.04, p<0.001], position 0.19 [±0.03, p<0.001], gene count 0.13 [±0.03, p<0.001], linkage disequilibrium 0.15 [±0.02, p<0.001], centromere 0.32 [±0.09, p<0.001]; d_{XY}: GC content -0.09 [±0.04, p=0.01], position -0.08 [±0.03, p<0.001], gene count 0.11 [±0.03, p<0.001], size 0.62 (±0.08, p<0.001], linkage disequilibrium 0.24 [±0.02, p<0.001], centromere 0.63 [±0.11, p<0.001]). Each predictor is scaled and their effects are plotted with other variables held at their medians.