

1 Full Title: Host diversity and behavior determine patterns of interspecies transmission and
2 geographic diffusion of avian Influenza A subtypes among North American wild reservoir
3 species

4 Short Title: Ecology and Evolution of Avian Influenza A virus in North American wild birds

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15 ABSTRACT

16 Wild birds can carry avian influenza viruses (AIV), including those with pandemic or panzootic
17 potential, long distances. Even though AIV has a broad host range, few studies account for host
18 diversity when estimating AIV spread. We analyzed AIV genomic sequences from North
19 American wild birds, including 303 newly sequenced isolates, to estimate interspecies
20 transmission and geographic diffusion patterns among multiple co-circulating subtypes. Our
21 results show high transition rates within Anseriformes and Charadriiformes, but limited
22 transitions between these orders. Patterns of interspecies transmission were positively associated
23 with breeding habitat range overlap, and negatively associated with host genetic distance.
24 Distance between regions (negative correlation) and summer temperature at origin (positive
25 correlation) were strong predictors of diffusion. Taken together, this study demonstrates that host
26 diversity and ecology can determine evolutionary processes that underlie AIV natural history and
27 spread. Understanding these processes can provide important insights for effective control of
28 AIV.

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31 INTRODUCTION

32 Avian influenza viruses (AIV) are globally distributed pathogens maintained within wild
33 waterfowl (order Anseriformes) and shorebirds (order Charadriiformes) (1). Despite being
34 largely asymptomatic within wild birds, AIV provide cause for global concern as sources of
35 influenza A viral diversity for domestic avian and mammalian hosts (2). AIV hemagglutinin
36 (HA) subtypes H5 and H7 have repeatedly evolved into highly pathogenic viruses in domestic
37 poultry causing devastating loss (3). Furthermore, all modern pandemic influenza viruses contain
38 gene segments of avian origin, suggesting reassortment with avian viruses plays a crucial role in
39 pandemic emergence (4). The segmented genome is an important characteristic of influenza
40 viruses because it facilitates continual reassortment and promotes diversity of AIV within wild
41 avian populations (1,5,6). AIV segments are habitually interchanging, existing as functionally
42 equivalent arrangements (5). Due to the unlinked nature of the AIV genes, each segment can be
43 considered as an independent hereditary particle with its own evolutionary history (7).

44 Understanding the host behavior and environmental drivers of AIV susceptibility and
45 dispersal remain a top priority for avian influenza surveillance, but the vast array of susceptible
46 host species and ecological variables hampers the prediction of AIV emergence and incidence
47 (8). Surveillance data and spatial analysis have begun to assess the association between avian
48 influenza prevalence and environmental variables, including land use (9,10), temperature
49 measures (9,11,12), altitude (10), distance to water (10), and precipitation (11). Fewer studies
50 have assessed the impact of host characteristics on the prevalence of AIV within individual avian
51 species although migration distance, habitat water salinity, and surface foraging methods have
52 been implicated as important predictors in one such study (13). Sequence data acquired by viral
53 surveillance provide further information to understand AIV dynamics. Because viral evolution,

54 host ecology, and environmental factors necessarily interact, phylogenetic studies can help
55 elucidate the paths of AIV dispersal (Figure 1). For example, previous phylogeographic analysis
56 (7) of AIV within North America provided evidence that migratory flyways are not as strong a
57 barrier to viral dispersal as previously believed (14).

58 Although phylogenetic studies to date have been able to interrogate the impact of broad
59 ecological patterns such as migratory flyways and interhemispheric viral exchange, few
60 incorporate characteristics of the location or host from which the virus was sampled. Prevalence
61 studies include these characteristics into regression and spatial models, but are limited due to the
62 long-distance migration of wildlife hosts. Generalized linear models (GLM) implemented within
63 a Bayesian phylogenetic framework have made it possible to include environmental and
64 ecological covariates into phylogenetic models (15,16). This allows the simultaneous inference
65 of viral transition rates among specified traits (i.e., hosts or locations) and their association with
66 covariates that may drive viral movement. This approach has been adapted to investigate the role
67 of anthropogenic and environmental variables on the diffusion of avian influenza within China
68 (17) as well as of avian influenza subtype H9N2 on a global scale (18). The GLM has also been
69 used to uncover the impact of host behavior on the dispersal of rabies virus among bat species
70 (19). Previous analyses have also demonstrated the importance of environmental transmission on
71 AIV prevalence and evolution (20,21), suggesting ecological factors may influence AIV
72 transmission. Understanding how avian host characteristics and environmental variables impact
73 zoonotic transmission and geographic dispersal will be key to identify surveillance priorities
74 among species and locations. In the presented analysis, using an extensive publicly-available
75 dataset of multiple AIV subtypes collected from North American wild birds supplemented with
76 newly sequenced surveillance samples, we implemented the GLM to assess the impact of

77 ecological and environmental characteristics on the dispersal of AIV across the North American
78 continent and among frequently sampled Anseriformes and Charadriiformes.

79 RESULTS

80 *Summary of Newly Sequenced Data*

81 Supplementary Table S1 describes the characteristics of 303 newly sequenced AIV
82 isolates, which originated from samples collected from wild birds between 2003 and 2016 in
83 Delaware Bay, New Jersey, United States (86.5%) and Alberta, Canada (13.5%). All sequenced
84 samples from Alberta were exclusively of waterfowl origin (order Anseriformes). Delaware Bay
85 samples originated almost exclusively from shorebirds (order Charadriiformes), except for a
86 single Canada goose (*Branta canadensis*) sample. Among all newly sequenced viral isolates,
87 most (60.4%) were isolated from samples collected from the ruddy turnstone (*Arenaria*
88 *interpres*), a migratory shorebird of the wader family with near global distribution and
89 intercontinental migration patterns. Nine samples were found to be co-infected with avian
90 paramyxovirus and were excluded from further analysis. The most frequently isolated
91 hemagglutinin (HA) subtype was H10 (27.4%), followed by H12 (18.8%) and H3 (9.2%). Most
92 HA subtypes were collected in Delaware Bay, including H1, H3, H5, H6, H7, H8, H9, H10, H11,
93 H12, H13, and H16. Only H4 was exclusively isolated from Alberta. The most frequent
94 neuraminidase (NA) subtypes were N5 (20.1%), N7 (13.9%), and N8 (13.5%). All but two NA
95 subtypes were isolated from both Delaware Bay and Alberta; N3 and N9 were only recovered
96 from Delaware Bay.

97 *Evolutionary Comparison Between Segments and Subtypes*

98 The newly sequenced data were aligned with publicly available sequences and
99 subsampled in two methods to help address sampling biases in surveillance: a phylogenetic

100 diversity-based analysis method (PDA sample) and a simple stratified random sample method
101 (stratified sample). Evolutionary models were constructed separately for each gene segment; HA,
102 NA, and NS segment datasets were further subdivided by subtype or allele. Because the PDA
103 sample maintains the total genetic diversity of the original sample, the evolutionary parameters
104 of the PDA sample are discussed here. In general, the two samples produced similar comparative
105 relationships of evolutionary parameters among the analyzed gene segments; however, the
106 stratified sample had consistently lower molecular clock rates and effective population sizes
107 compared to the PDA sample (Supplementary Figure S1). Compared with the HA and NA
108 surface proteins, the internal gene segments tended to have older times to the most recent
109 common ancestor (TMRCA) (Supplementary Figure S1A; Supplementary Table S2), except the
110 included sequences of the NS gene B allele, which shared a common ancestor around 1965 (95%
111 Highest Posterior Density Bayesian Credibility Interval (HPD) 1958.5 – 1969.7). HA and NA
112 genes tended to have a TMRCA within the mid- to latter-half of the twentieth century, although
113 this pattern deviated for H3 and N3, which had TMRCA older than other HA and NA subtypes
114 (H3: 1929.0, 95% HPD 1900.0 – 1948.5; N3: 1895.6, 95% HPD 1830.8 – 1944.7). The
115 uncertainty of the N3 subtype TMRCA is most likely due to the lack of older sequences which
116 would help calibrate the divergence time of apparent Eurasian-origin viruses that circulate in
117 North America.

118 As compared to the HA and NA surface proteins which contend with greater selection
119 pressure, the internal gene segments tended to have slower evolutionary rates as measured by the
120 mean substitution rate of the uncorrelated relaxed molecular clock (Supplementary Figure S1B;
121 Supplementary Table S2). The two NS alleles had differing substitution rates with the A allele
122 evolving faster (3.4×10^{-3} substitutions/site/year; 95% HPD 3.0×10^{-3} – 3.7×10^{-3}) compared to the

123 B allele (2.6×10^{-3} substitutions/site/year; 95% HPD $2.3 \times 10^{-3} - 2.9 \times 10^{-3}$). In comparison to the
124 internal gene segments, the HA and NA surface proteins were estimated to have more variable
125 substitution rates with median rates ranging from 2.5×10^{-3} (H3) to 5.8×10^{-3} (H7)
126 substitutions/site/year. Six of the eight analyzed HA subtypes had estimated median substitution
127 rates above 3.8×10^{-3} substitutions/site/year. In contrast, H3 and H4 were estimated to have much
128 slower substitution rates at 2.5×10^{-3} (95% HPD $2.2 \times 10^{-3} - 2.7 \times 10^{-3}$) and 2.8×10^{-3} (95% HPD
129 $2.6 \times 10^{-3} - 3.1 \times 10^{-3}$) substitutions/site/year, respectively. The NA subtype with the fastest
130 substitution rate was N7 (5.0×10^{-3} substitutions/site/year; 95% HPD $4.4 \times 10^{-3} - 5.6 \times 10^{-3}$).

131 Internal gene segments were estimated to be sustained by a much larger effective
132 population size as compared to the surface proteins (Supplementary Figure S1C; Supplementary
133 Table S2). NS alleles differed from the remaining internal gene segments, with median effective
134 population sizes around half that of PB2, PB1, PA, NP, and MP segments. Similarly, the
135 effective population sizes of the various HA and NA subtypes were considerably lower than that
136 of the non-subdivided internal gene segments. Because the genetic diversity of the NS, HA, and
137 NA gene segments was divided between datasets, lower population sizes are needed to explain
138 the observed viral circulation. Variation among HA and NA subtypes was also noted. Most HA
139 subtypes were estimated to have median effective population sizes below 20, but those of H3 and
140 H4 were substantially larger (H3: 99.3, 95% HPD 87.2 – 112.5; H4: 78.0, 95% HPD 68.3 –
141 88.2). The effective population sizes of the NA subtypes also varied considerably with median
142 sizes ranging from 8.5 (N7) to 85 (N8).

143 *Discrete Trait Diffusion Models*

144 Two discrete trait diffusion models were estimated for each of 22 gene segment or
145 subtype datasets to assess how AIV disperses among host species and geographic regions of

146 North America. North American regions were categorized into eight Canadian provinces and
147 territories (Alberta, British Columbia, New Brunswick, Newfoundland and Labrador, Nova
148 Scotia, Ontario, Prince Edward Island, and Quebec), ten United States climate regions (Alaska,
149 Midwest, Northeast, Northwest, Ohio Valley, Northern Rockies and Plains, South, Southeast,
150 Southwest, and West), one Mexican state (Sonora), and Guatemala. Represented host species
151 were of the taxonomic orders Anseriformes (waterfowl) and Charadriiformes (shorebirds). The
152 16 Anseriformes species included American black duck (*Anas rubripes*), bufflehead (*Bucephala*
153 *albeola*), blue-winged teal (*Anas discors*), Canada goose (*Branta canadensis*), cinnamon teal
154 (*Anas cyanoptera*), emperor goose (*Anser canagicus*), gadwall (*Mareca strepera*), greater white-
155 fronted goose (*Anser albifrons*), green-winged teal (*Anas crecca*), mallard (*Anas platyrhynchos*),
156 northern pintail (*Anas acuta*), redhead (*Aythya americana*), ring-necked duck (*Aythya collaris*),
157 northern shoveler (*Anas clypeata*), snow goose (*Anser caerulescens*), and American wigeon
158 (*Anas americana*). Five species of Charadriiformes were represented among the host models:
159 glaucous-winged gull (*Larus glaucescens*), laughing gull (*Leucophaeus atricilla*), red knot
160 (*Calidris canutus*), ruddy turnstone (*Arenaria interpres*), and sanderling (*Calidris alba*).
161 Henceforth, all host species will be referenced using common names.

162 The distribution of hosts and geographic regions were similar among the internal gene
163 segments by both PDA and stratified subsampling strategies (Supplementary Table S3;
164 Supplementary Table S4). Subsampling strategy had an effect on the temporal distribution of
165 host and geographic region variables; proportions were more consistent between 2005 and 2016
166 in the stratified sample compared with the PDA sample (Supplementary Figures S2 & S3).
167 Within both the PDA and stratified samples, Alaska, the Ohio Valley, and the Northeast were the
168 most frequently represented regions between 2005 and 2016 among the internal genes. Regional

169 distribution varied considerably across HA and NA subtypes. Within the PDA sample, the most
170 frequently represented regions' HA subtypes included Alaska (H3: 30.5%, H4: 20.5%),
171 Northeast (H1: 20.7%, H10: 31.1%, H11: 20.0%), South (H7: 23.7%), and West (H5: 20.5%,
172 H6: 28.1%, H11: 20.0%). The most frequently represented regions among NA subtypes in the
173 PDA sample included Alaska (N3: 18.3%, N6: 25.9%, N8: 24.5%), Midwest (N2: 20.3%, N9:
174 20.3%), and Northeast (N1: 19.2%, N7: 25.2%). Although host species distribution differed
175 among gene segments and subtypes, all shared mallard as the most frequently sampled avian
176 species (28.1 – 52.7%). The stratified sample attempted to counteract the oversampling of
177 mallards resulting in lower percentages of these hosts within the sample (20.6 – 35.7%). The
178 stratified method also tended to increase the frequency of the more sparsely represented regions
179 and hosts within the models.

180 Asymmetrical diffusion models allow directionality to be inferred so that each viral
181 transition is characterized by a source (i.e., origin of the virus) and a sink (i.e., destination).
182 Because the rates of transition between two locations, for instance, are asymmetrical, the
183 transition rate from location A to location B is permitted to differ from the rate in the opposing
184 direction (from location B to A). Across all gene segments, the highest rate of transition between
185 host species was 19.6 transitions/year (95% HPD 16.0 – 23.6) of the PB1 gene segment from
186 mallards to blue-winged teals within the PDA sample (Supplemental Figure S4). In the PDA
187 sample, the N8 transition rate from mallards to blue-winged teals was highest among the NA
188 subtypes at 13.3 transitions/year (95% HPD 9.3 – 17.7). In contrast, among HA subtypes, the
189 reverse transition (that is, blue-winged teals to mallards) within the PDA H4 model had the
190 highest rate (16.1 transitions/year; 95% HPD 10.9 – 21.4). Mallards were supported as the source
191 of AIV across all gene segments and subtypes for green-winged teals and northern shovelers

192 within the stratified sample. These rates were also supported in the PDA sample in all gene
193 segments and subtypes except N6. The rates from mallards to blue-winged teals were also
194 supported among all gene segments and subtypes except H7 in both samples. Within the PDA
195 sample, American black ducks, blue-winged teals, Canada geese, greater white-fronted geese,
196 ring-necked ducks and snow geese were only supported to receive viral diversity from mallards.
197 In contrast, only American black ducks and Canada geese exclusively received virus from
198 mallards in the stratified sample. Similarly, ruddy turnstones were the exclusive source of viral
199 diversity for laughing gulls and sanderlings in both samples, as well as red knots in the stratified
200 sample.

201 A single host diffusion model was also jointly estimated across all internal gene
202 segments, all HA subtypes, and all NA subtypes (Figure 2, Supplementary Figure S5). For each
203 joint host model, the highest transition rate occurred from blue-winged teals to mallards (PDA
204 internal gene model: 40.7 transitions/year, 95% HPD 32.5 – 49.2; PDA HA model: 22.0
205 transitions/year, 95% HPD 16.6 – 27.5; Stratified NA model: 22.6 transitions/year, 95% HPD
206 14.2 – 31.7; Tables S5, S6 & S7). In all three joint host models, all species were supported as
207 receiving virus from at least one other species, except snow geese within the NA models. Not all
208 species acted as a source, however. Cinnamon teals, gadwalls, and red knots were included in all
209 three joint host models, but none were supported to contribute AIV genetic diversity to any other
210 host species. In addition, Canada geese, emperor geese, ring-necked ducks, snow geese, laughing
211 gulls, and sanderlings, which were only included in the internal gene and NA models, were also
212 not supported as viral sources. A marked difference between the PDA and stratified samples can
213 be noted in this regard. Whereas green-winged teals were not supported as a source of virus for
214 any other species within the PDA internal gene segment model, the stratified sample estimates

215 green-winged teals as the source of viral genetic diversity for nine other avian species within the
216 internal gene model. This provides evidence that sampling methods can influence discrete trait
217 diffusion model results.

218 Among the North American regional models, the highest transition rate was observed
219 from the Ohio Valley to the South within the PA gene segment of the PDA sample at a rate of
220 23.3 transitions/year (95% HPD 17.6 – 29.0; BF = 73,262) (Figure S6). In the PDA sample, the
221 N6 model showed the highest transition rate of the NA subtypes with a Midwest to South
222 transition rate of 11.4 transitions/year (95% HPD 7.5 – 15.7; BF = 46,210). Within the stratified
223 sample, the highest transition rate among HA subtypes occurred from the Midwest into the Ohio
224 Valley in the H4 model at 14.9 transitions/year (95% HPD 9.9 – 20.1, BF = 46,210). No single
225 transition rate was supported across all gene segments or subtypes. The internal gene segments
226 and the HA and NA subtype models differed in regard to support for the Northeast region of the
227 United States as a source of AIV for other North American regions. Across the HA and NA
228 subtypes, there is only sporadic support for the Northeast as a source of AIV, with only three
229 rates among the subtypes supported in the PDA sample, and four supported in the stratified
230 sample. In contrast, each internal gene segment model within the PDA sample has at least six
231 rates in support of the Northeast as a source. Support for a Northeastern source is less consistent
232 across the stratified sample internal gene segments: while nine rates are supported in the PB2
233 model, no rates in the PB1 model are supported. The internal genes further differ between PDA
234 and stratified samples in terms of their support for New Brunswick as a viral source. No New
235 Brunswick source rates are supported within the PDA internal gene segment models, yet 16 rates
236 are supported in the stratified models among four sink regions (Northeast, Nova Scotia, Ohio
237 Valley, and Prince Edward Island).

238 Among the three joint models, the internal gene model has the largest number of
239 decisively supported transition rates between regions (Figure 2, Supplementary Figure S5). The
240 highest rate among the internal genes occurred from the South to the Ohio Valley (PDA sample:
241 48.5 transitions/year, 95% HPD 42.5 – 55.0; Table S8). The highest transition rate among both
242 HA and NA models occurred from the Midwest to the Ohio Valley (stratified HA: 17.8
243 transitions/year, 95% HPD 12.7 – 23.4; PDA NA: 21.3 transitions/year, 95% HPD 16.7 – 26.2;
244 Tables S9 & S10). Similar patterns can be observed across the three models. For instance, due to
245 their frequent support and large transition rates, the West, Midwest, South, and Ohio Valley all
246 appear to be important regions in the dispersal of AIV across the North American continent.
247 Furthermore, while most decisively supported rates are between neighboring regions, longer
248 distance transitions are also observed in all three models, including between the West and
249 Alaska, the South and Guatemala, and the West and the Ohio Valley. Many supported rates also
250 align with an East-West axis, suggesting viral exchange across migratory flyways.

251 *Generalized Linear Model*

252 The discrete trait diffusion models were extended with a GLM to evaluate the impact of
253 host and geographic ecological characteristics on AIV dispersal among host species and
254 geographic regions within North America. Table 1 summarizes host species and regional
255 characteristics included in the GLM. Genetic distance of host species ranged widely, from 0.3 to
256 196.7 million years (Figure 3). As expected, the host phylogeny is composed of two main clades,
257 Anseriformes and Charadriiformes, which diverged between 86.6 and 110.2 million years ago.
258 Included Charadriiformes species shared a most recent common ancestor between 46.0 and 64.2
259 million years ago, whereas Anseriformes species diverged into familial clades of Anatidae
260 (ducks) and Anser (geese) between 10.0 and 31.4 million years ago. All nodes within the

261 phylogeny were highly supported (posterior probability > 0.98) except for the ancestral node of
262 the green-winged teal and Northern pintail (posterior probability = 0.67). Host habitat
263 distributions tended to have greater percentage of overlap during the nonbreeding winter months
264 versus the breeding summer months. Migration propensity and distance were calculated based on
265 distribution maps and varied widely among included species. On average, 84% of a species'
266 breeding season distribution was considered migratory as opposed to resident. The average
267 distance between North American geographic regions was 2,716 km, and geographic regions
268 overlapped with 47% and 48% of the breeding and nonbreeding distributions, respectively.
269 Regions tended to have greater precipitation, lower humidity, and more lush vegetation during
270 the summer months compared to the winter months. Variables such as host genetic relatedness,
271 habitat overlap, and geographic distance reflect the relationship between two variables, whereas
272 the remaining ecological variables summarize aggregate measurements. For this reason, the
273 relational variables were only included in the GLM once, but the remaining characteristics were
274 each included twice to capture directionality of the viral transition rate. For instance, the average
275 temperature during the summer months was included twice to assess if the summer temperature
276 of the source region was associated with viral transition or if the summer temperature of the sink
277 region impacted viral transition.

278 The host and region GLM models tested the same covariates across all gene segments
279 and subtypes, individually. Overall, the internal gene segments held higher support for the
280 inclusion of both host and region covariates as compared to the HA and NA subtype models
281 (Figure 4). On average 20 of the 32 tested variables were supported for inclusion among the
282 internal gene segments compared to five and seven supported variables among HA and NA
283 subtypes, respectively. In the PDA sample, the H5 and N7 subtype models each supported only

284 one variable across both host and region GLMs. Nonbreeding distribution overlap and migratory
285 distance of the sink host species, as well as summer distribution overlap of the source region,
286 winter temperature of both source and sink regions, winter precipitation of both source and sink
287 regions, and winter humidity of source regions tended to have lower support among internal gene
288 segment models. Overlap of host breeding distribution was supported across all gene segments
289 and subtypes except H5 in both PDA and stratified samples and N6 in the PDA sample. Regional
290 distance was also frequently supported across the gene segments and subtypes, with support in
291 all but H10, N1, and N7 in both samples as well as H11 in the stratified sample. Summer
292 temperature of the source region was supported in both samples for all internal gene segments as
293 well as subtypes H1, H3, H4, H11, N2, and N3. Host genetic relatedness was supported in all
294 internal gene segments and all but two NA subtypes, N7 and N9, yet there was no support for
295 this variable among HA subtypes.

296 The magnitude and direction of variable effect size differed among the various gene
297 segments although most variables demonstrated the same directional effect across multiple gene
298 segments. Among the variables supported in the models, 22 had the same directional effect
299 (positive or negative) without regard to gene segment or subtype. Host variables which were
300 consistently positively-associated with interspecies transmission included breeding distribution
301 overlap, nonbreeding latitude and migration distance of the source host. Consistent negatively-
302 associated host characteristics included genetic distance between host species and migration
303 propensity of both the source and sink host species. Among North American regional geographic
304 models, the proportion of avian hosts in source regions with summer distribution overlap , the
305 proportion of avian hosts in sink regions with winter distribution overlap , both source and sink
306 summer temperature measures, and source summer normalized difference vegetation index

307 (NDVI) were positively associated with viral dispersal across all segments and subtypes in which
308 the variables had support for inclusion. The following region characteristics were consistently
309 negatively-associated with viral dispersal: distance between regions, summer precipitation of the
310 sink region, and both winter NDVI measures. Several directional effects conflicted among
311 subtypes and gene segments, including nonbreeding distribution overlap, nonbreeding latitude of
312 the sink host, summer habitat overlap in the sink region, summer precipitation of the source
313 region, winter precipitation of the sink region, summer humidity of the sink region, winter
314 humidity of the source region, and summer NDVI of the sink region. These conflicts tended to be
315 observed in variables with infrequent support, especially within the stratified sample.

316 DISCUSSION

317 The presented analysis provides insight into the potential impact of ecological variables
318 that influence AIV dispersal and diversity within North American wild birds. While the
319 evolution and dispersal of AIV within North America has been previously examined
320 (7,8,14,22,23), this study employs a discrete trait diffusion GLM to incorporate ecological data
321 into such estimates. Using new and historical AIV sequences, we demonstrate that host and
322 geographic characteristics are associated with viral movement among avian species and North
323 American regions. Because AIV gene segments can be treated as independent hereditary
324 particles, genetic similarities can be used to infer information regarding the ecological pressures
325 experienced by viral populations. By estimating ecological models separately for each AIV gene
326 segment, dispersal patterns and their associations with ecological characteristics can be tested
327 independently and compared. Consistent support for a variable across multiple gene segments
328 and subtypes, such as breeding distribution overlap and geographic distance between regions,
329 suggest that these host habitat characteristics play an important role in the evolution and ecology

330 of AIV. Although AIV hosts often migrate and potentially carry virus over long distances, a
331 geographic distance effect can be noted: as the distance between two regions increases, the
332 frequency of AIV transition decreases. The importance of proximity is reinforced by the
333 consistent support of distribution overlap, particularly in the summer breeding season. A similar
334 finding has been observed in bats, in which viral transmission of rabies virus was associated with
335 host distribution overlap in North America (19). Species that have greater overlap during the
336 breeding months tend to have a higher frequency of AIV transition due to a larger population of
337 immunologically naïve juvenile hosts.

338 Another frequently supported host characteristic is the genetic distance or relatedness
339 between two species, a characteristic that has been suggested to influence the rate of interspecies
340 transmission of pathogens in general (24). Genetic relatedness may be a proxy for a suite of
341 shared characteristics that would increase the likelihood of two hosts sharing a pathogen. For
342 instance, viruses that infect multiple species are most likely targeting conserved molecular
343 mechanisms, and related hosts will most likely have similar physiological responses (25).
344 Furthermore, related species typically share similar ecology, i.e. breeding and feeding behavior
345 or habitat, which can increase the likelihood of contact between the two species, a prerequisite
346 for pathogen transmission. Experimental studies (26) and mathematical models (27) have shown
347 that host relatedness is associated with successful host transition. Genetic distance, however,
348 was not supported among any of the HA models. The HA models in general tended to have
349 lower frequency of support for the included GLM models. This may suggest that the host
350 immune pressure exerted on the HA supersedes influence of ecological determinants. In other
351 words, because HA subtypes exist as a constellation of fitness peaks, these genes may be unable
352 to provide information on ecological factors that affect viral transmission. Rather they are

353 coerced by immune pressure to constantly accumulate mutations that provide fitness advantages
354 to evade host immune systems.

355 Somewhat surprisingly, summer temperature of the originating region was positively
356 associated with viral dispersal among regions in multiple gene segments. Environmental
357 durability experiments (28,29) and AIV prevalence studies (11,12) have demonstrated evidence
358 that colder temperatures increase risk of AIV infection due to environmental persistence of the
359 virus. In contrast, our geographic model suggests that regions that are warmer on average during
360 the summer are more likely to act as sources of the virus to other regions. It should be noted that
361 causality cannot be established for this association. Proper interpretation of this result is that
362 warmer regions are merely associated with viral dispersal, not that virus is more likely to arise
363 from regions during summer. Summer temperature may be a proxy for other environmental or
364 temporal characteristics. The effect of temperature on AIV dispersal can also be observed in the
365 host models in which latitude of the breeding distribution was negatively associated with viral
366 transitions between host species. In other words, species that breed farther south were more
367 likely to act as sources of AIV diversity to other host species. Similarly, species that overwinter
368 farther north were also more likely to act as sources of the virus. In corroboration with our
369 model, one prevalence study (9) revealed an earlier thaw date of a location to be associated with
370 higher AIV prevalence. Our results may be best explained by timing of breeding and migration
371 rather than environmental persistence alone. Those locations that thaw first (i.e., are warmer in
372 general) become available as breeding habitat sooner than regions farther north. Because
373 breeding marks the influx of new, immunologically naïve juveniles, populations that breed
374 earlier tend to become infected earlier, which may increase their capacity to serve as a source of
375 virus to other hosts and locations.

376 As with analyses reliant on publicly available data, these results are limited by potential
377 sampling bias of available surveillance and sequence data. As demonstrated, mallards markedly
378 dominate the diffusion models as sources of virus to other species. Mallards are the most
379 populous of the dabbling ducks and therefore are more frequently included in AIV surveillance,
380 but they are often also the species with the highest prevalence of AIV (30). While one
381 explanation for the estimation of mallards as frequent viral sources is their predominance in
382 surveillance, the analysis methods were intended to limit the effects of sampling biases.
383 Sequences collected prior to 2005 when sequencing efforts were irregular were not permitted to
384 influence the discrete trait diffusion models. Further, by subsampling the datasets based on
385 phylogenetics, we preserved the genetic diversity of the sequence data. The fact that mallards
386 predominate in the PDA sample suggests that, as a primary reservoir species, mallards harbor a
387 large diversity of AIV. A second subsampling technique (stratified random sample) was also
388 performed in attempt to limit oversampling bias and increase the frequency of underrepresented
389 hosts and regions. By comparing results between the two datasets, the influence of sampling
390 schemes on the observed results can be approximated. Estimating the models across multiple
391 gene segments and subtypes also allowed the host and regional proportions to vary, which is
392 more apparent among the HA and NA subtypes. It should be noted that the magnitude of the
393 effective population size across all segments tracked closely with the sample size of sequences
394 included within the analysis. As the sample size was proportional to the number of available
395 sequences that met inclusion criteria, the sample size may indicate the overall genetic diversity
396 available for analysis, which would then be reflected in the estimated effective population size.
397 This is supported by the use of phylogenetic diversity as a means to sub-sample the data, which
398 ensures that both the full available sequences and the sampled sequences would have equivalent

399 genetic diversity, unlike a simple random sample which, by chance, may remove some genetic
400 diversity.

401 Although causality between ecologic factors and AIV diffusion cannot be inferred from
402 this analysis, our results provide further evidence of the association of geographic and host
403 characteristics with AIV diversity and dispersal. Continued AIV surveillance, especially in
404 undersampled regions and hosts, provides valuable information on AIV evolution and diffusion.
405 Furthermore, the inclusion of detailed environmental and host measures within AIV sequence
406 databases will help add granularity to future models.

407 MATERIALS AND METHODS

408 *Sequence data sets*

409 Systematic avian influenza surveillance of wild birds has been performed in Alberta,
410 Canada and Delaware Bay, New Jersey, United States since 1976 and 1985 respectively.
411 Surveillance efforts, viral isolation, and genomic sequencing methods were performed as
412 previously described (7). Newly sequenced genomes from 303 viral isolates were deposited in
413 GenBank (Supplementary Table S11) and were aligned with publicly available AIV sequences
414 from within North America between 1970 and 2016, which were downloaded from the Influenza
415 Research Database (IRD; www.fludb.org) on March 26, 2018. Sequences with vague host (e.g.,
416 “avian,” “bird,” “duck,” etc.) or location (i.e., only country level data for the United States,
417 Canada, or Mexico), more than 10% missing nucleotide sites, or isolated from domestic poultry
418 were removed from the dataset. Internal gene segments PB2, PB1, PA, NP, and MP were aligned
419 separately. Alignments of gene segments NS, HA, and NA were further subdivided: NS by allele
420 group (A and B) and HA and NA by subtype. HA and NA subtypes with sparse representation
421 (<250 sequences between 2005 and 2016) were excluded from the analysis (subtypes H2, H8,

422 H9, H12, H13, H14, H16, N4, N5). Initial maximum likelihood phylogenetic trees were
423 estimated using RAxML v8 (31) with a general time reversible nucleotide substitution model and
424 gamma distribution of sites. TempEst v1.5 (32) was used to identify sequences with a rate of
425 evolutionary divergence out of the expected bounds as compared to the remaining sequences in
426 the dataset. This helps to identify poor quality sequences or viruses under unexpected
427 evolutionary pressure. Eurasian lineages with little continued North American circulation or
428 associated with highly pathogenic avian influenza viruses were removed from the dataset. For
429 each sequence, host of origin was categorized based on host species. Location of origin was
430 categorized based on United States National Oceanic and Atmospheric Administration historical
431 climate region for United States isolates, province and territory for Canadian isolates, state for
432 Mexican isolates, and country for Guatemalan isolates. Categories to be included in the discrete
433 trait models were determined separately for the internal genes, HA subtypes, and NA subtypes.
434 For internal genes, the 20 most common host species and regions (based on average rank among
435 the segments) were chosen to be included in the discrete trait diffusion models. For both HA and
436 NA subtypes, categories with greater than one sequence in a majority of the HA or NA subtypes
437 were included in the models.

438 All sequences collected before 2005 were combined into a single category that was
439 masked in the diffusion models to prevent the influence of inconsistent sampling and to focus
440 diffusion summaries on the most recent years. To mitigate oversampling, two subsampling
441 schemes were used: simple stratified random sampling and phylogenetic diversity-based
442 sampling. In the simple random sample, sequences were stratified by region, host species, and
443 year, and a maximum sample size of three sequences for each stratum were maintained in the
444 dataset. Developed to help make economic decisions for conservation purposes, Phylogenetic

445 Diversity Analyzer (PDA; <http://www.cibiv.at/software/pda/>) was used to select a subsample for
446 each segment or subtype that maximized the represented genetic diversity (33). This process was
447 weighted to prevent over-representation of samples before 2005 which, though diverse, were
448 masked in the diffusion model. As PDA allows the user to select the desired sample size, the
449 number of selected sequences was specified to match the stratified sample and ensure datasets
450 were proportional.

451 *Phylogenetic analysis*

452 Using ModelFinder algorithm (34) implemented in the program IQTree
453 (<http://www.iqtree.org/>), the best fit nucleotide substitution model was determined. The
454 empirical sets of phylogenetic trees were estimated under the same model assumptions for all
455 sequence datasets in BEAST v1.10.4 (35). A general time reversible (GTR) nucleotide
456 substitution model (36–38) with a 4-category gamma distribution of variation among sites and a
457 proportion of invariant sites (39,40) was implemented with a lognormal uncorrelated relaxed
458 molecular clock (41) (mean clock rate prior distribution: uniform 0 – 1, initial value = 0.0033)
459 and a constant coalescent population model (42,43) (population size prior distribution: lognormal
460 distribution with mean = 50 and standard deviation = 50). At least four independent Markov
461 chain Monte Carlo (MCMC) runs of 100 million state length and sampling every 10,000 states
462 were performed. To ensure proper convergence and parameter mixing with an effective sample
463 size (ESS) of at least 200, a minimum of 10% burn-in was removed. Non-convergent runs were
464 discarded, larger burn-in percentages were removed, and additional MCMC runs were performed
465 to achieve ESS > 200. Empirical tree sets were obtained by combining and resampling tree log
466 files from non-discarded runs with LogCombiner to achieve a tree file length of at least 1,500
467 trees.

468 *Discrete trait diffusion models*

469 With the ability to incorporate ecological and epidemiological metadata, the discrete trait
470 diffusion model uses a continuous-time Markov chain as its basis to estimate the ancestral
471 history of trait changes across a phylogenetic tree, in essence treating the trait as a characteristic
472 that evolves over time (44,45). To investigate recent movement of AIV among avian hosts and
473 North American regions, discrete trait diffusion models based on the empirical tree sets
474 described above were estimated using BEAST v1.10.4. Estimating the posterior distribution of
475 phylogenetic trees based on sequence data alone can be performed separately from the discrete
476 trait diffusion models because the discrete traits represent only two sites (as opposed to the
477 hundreds of nucleotide sites of a genetic sequence) at which the tree likelihood can be calculated.
478 For this reason, the discrete trait model has an insignificant impact on phylogenetic estimation
479 (16). Furthermore, this approach enables the inference of a single diffusion model across
480 multiple empirical tree sets, allowing the genetic information from multiple gene segments to
481 inform the model. Due to the high level of reassortment of gene segments within low pathogenic
482 AIV in wild birds (5), each gene segment can be treated as an independent hereditary particle,
483 providing separate evolutionary and ecological information within its phylogenetic history (7).
484 Asymmetrical discrete trait diffusion models were estimated across empirical tree sets for the
485 following: 1) each gene segment or subtype dataset individually, 2) all internal gene segments
486 together, 3) all represented HA subtypes together, and 4) all represented NA subtypes together.
487 Discrete host and geographic traits were specified as described above. Pre-2005 sequences and
488 rare categories were masked from the discrete trait diffusion model, providing an estimate of
489 viral transitions between common host species and regions between 2005 and 2016.

490 The discrete trait diffusion models were extended using a generalized linear model
491 (GLM) to evaluate predictors associated with the discrete trait transition rates among host
492 species and geographic regions. Using the transition rates as the outcome to a log-linear
493 combination of covariate predictors, BEAST v1.10 estimates the GLM at each state in the
494 MCMC simulation, integrating across the empirical phylogenetic tree space. Host diffusion
495 predictors included genetic distance between species, habitat distribution overlap, migration
496 distance, migration propensity, and latitudinal distribution. Genetic distance between species was
497 calculated as the average patristic distance, represented as total evolutionary time in million
498 years, across a sample of 1,000 phylogenetic trees estimated under a fossil-calibrated relaxed
499 molecular clock (46). Habitat overlap, migration distance, migration propensity, and latitudinal
500 distribution were summarized from BirdLife species range maps (47) using ArcGIS Pro
501 software. Habitat distribution overlap was calculated as the percentage of a source host's
502 geographic distribution shared with that of a sink host. Migration distance was estimated by the
503 difference between the mean breeding distribution latitude and the mean wintering distribution
504 latitude (13). Migration propensity was estimated as the percentage of total summer distribution
505 range considered to be migratory as opposed to resident (13). Latitudinal distribution was the
506 average latitude for breeding and wintering ranges and served as an estimate of habitat
507 temperature. Geographic diffusion predictors included distance between regions as well as
508 summer and winter summaries of each of the following: average temperature, average
509 precipitation, average relative humidity, average normalized difference vegetation index (NDVI),
510 and proportion of included host species that reside in the region. All geographic variables were
511 summarized between 2005 and 2016 and aggregated in ArcGIS Pro. Climatological data
512 originated from the National Centers for Environmental Prediction North American Regional

513 Reanalysis (48) provided by the National Oceanic and Atmospheric Administration Oceanic and
514 Atmospheric Research Earth System Research Laboratory's Physical Sciences Division,
515 Boulder, Colorado, USA, from their website at <https://www.esrl.noaa.gov/psd/>. NDVI data
516 originated from the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation
517 Indices (MOD13A3) Version 6 (49). All covariates were log-transformed and standardized
518 before inclusion in the GLM. Each discrete trait diffusion model and GLM were performed with
519 at least three independent MCMC runs of 1 million chain length sampling every 100 states.

520 *Statistical analysis*

521 For both the discrete trait diffusion model and the GLM, Bayesian stochastic search
522 variable selection (BSSVS) was used to estimate the statistical support for diffusion rates and
523 coefficients, respectively, by enabling the calculation of a Bayes factor (BF) (50). A larger BF
524 indicates stronger support that the parameter (i.e., transition rate between two hosts or GLM
525 coefficient) is non-zero. Due to the number of models tested, a stringent statistical cutoff was
526 implemented, only allowing those with $BF > 100$ to signify statistical support. Median
527 conditional transition rates, median conditional coefficients, 95% highest posterior density
528 (HPD) intervals, and BF were calculated from BEAST posterior samples with personalized
529 Python scripts using the PyMC3 package for Bayesian statistical modeling (51).

530 DATA AVAILABILITY

531 Newly sequenced AIV nucleotide sequences have been deposited in GenBank with
532 accession numbers provided in Supplementary Table S11.

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727 TABLES

728 Table 1. Summary of host and geographic variables used to inform the Bayesian discrete
729 diffusion generalized linear model describing avian influenza virus dispersal among North
730 American wild birds.

	Mean	Standard Deviation	Range
Genetic Distance (Myr)	92.9	83.4	0.3 – 196.7
Summer Distribution Overlap (%)	26.6	32.0	0.0 – 99.99
Winter Distribution Overlap (%)	40.9	32.2	0.0 – 99.6
Breeding Latitude	56.4	11.7	28.0 – 76.7
Nonbreeding Latitude	34.1	8.3	21.6 – 56.6
Migration Distance (km)	2469.2	1447.9	473.8 – 5651.8
Migration Propensity (%)	84.4	22.1	18.1 – 100.0
Geographic Distance (km)	2716.9	1342.2	138.5 – 7087.5
Summer Proportion (%)	46.7	20.3	0.0 – 85.7
Winter Proportion (%)	48.1	28.2	0.0 – 90.5
Summer Temperature (C)	19.7	5.1	11.0 – 28.9
Winter Temperature (C)	-2.7	9.4	-15.6 – 19.7
Summer Precipitation (kg/m ²)	2.7	1.4	0.3 – 7.5
Winter Precipitation (kg/m ²)	1.9	0.9	0.4 – 3.4
Summer Humidity (%)	66.9	15.7	31.4 – 86.1
Winter Humidity (%)	78.1	10.6	47.4 – 86.3
Summer NDVI*	0.63	0.16	0.31 – 0.82
Winter NDVI*	0.29	0.16	0.02 – 0.75

731 *NDVI – Normalized difference vegetation index

732

733 FIGURE CAPTIONS

734 Figure 1. Interaction of viral evolution, host ecology and the environment. Viral genetic
735 sequences contain information regarding virus evolution and diversity (A). Because their
736 evolution occurs at a rapid pace, evolutionary patterns can be used in conjunction with location
737 and species data to infer rates of viral dispersal among sampled geographic regions and host
738 species. Many factors may influence observed virus transmission and spread. For instance, host
739 factors (B) such as relatedness of host species and overlap of habitat distributions may be
740 associated with viral transitions between host species. Further, environmental factors (C) may
741 also play a role in the spatial diffusion of the virus. By incorporating viral, host and
742 environmental information into computational models, the impact of host and environmental
743 characteristics on virus spread can be estimated.

744 Figure 2. Discrete trait diffusion models of North American avian influenza using a sample of
745 genetic sequences based on phylogenetic diversity. Host models (left) are presented for
746 combined internal gene segment (A), hemagglutinin gene subtype (B), and neuraminidase gene
747 subtype (C) models. Source host species on the left of the chord diagrams contribute viral
748 diversity to sink host species on the right. The magnitude of the viral transition rate is
749 proportional to the width of the band, and statistically supported rates are darkened. Bands are
750 colored by the host order of the source species (Charadriiformes – red; Anseriformes – blue).
751 Similarly, geographic models (right) are summarized for combined internal gene segment (D),
752 hemagglutinin gene subtype (E), and neuraminidase gene subtype (F) models. Arrow width is
753 proportional to the magnitude of the transition rate, and only statistically supported rates are
754 displayed. (AK – Alaska, AB – Alberta, BC – British Columbia, GT – Guatemala, MW –
755 Midwest, NB – New Brunswick, NE – Northeast, NL – Newfoundland and Labrador, NRP –

756 Northern Rockies and Plains, NS – Nova Scotia, NW – Northwest, OV – Ohio Valley, PE –

757 Prince Edward Island, QC – Quebec, S – South, SE – Southeast, SON – Sonora, SW –

758 Southwest, W – West)

759 Figure 3. Viral and host phylogenetic diversity of North American AIV. (A) Estimation of the

760 phylogenetic history of the PB2 AIV gene segment within North American wild birds. Color

761 bands at the tips of the tree denote the host species distribution. This is contrasted with the

762 phylogenetic history of the avian host species included in this analysis (B). Light gray node bars

763 represent the 95% highest posterior density of the node height. The redhead species was not

764 categorized in the internal gene segment models and is therefore not included.

765 Figure 4. Heat map of conditional coefficient values for host and region generalized linear

766 models of North American avian influenza discrete trait diffusion models. Conditional

767 coefficient effect sizes are presented for each supported ecological variable across all gene

768 segment and subtype datasets and both subsampling strategies (phylogenetic diversity analyzer

769 (PDA) vs. stratified random sample). Only supported coefficients are displayed. Color darkness

770 is proportional to the magnitude of the effect. Orange represents a negative correlation and blue

771 represents a positive correlation.

772

773 SUPPLEMENTARY MATERIAL CAPTIONS

774 Figure S1. Evolutionary parameter estimation for North American avian influenza viruses of
775 wild birds. Estimated parameters include A) time to most recent common ancestor (TMRCA), B)
776 molecular clock rate, and C) effective population size. Parameters are compared across internal
777 gene segments (blue), hemagglutinin gene subtypes (orange), and neuraminidase gene subtypes
778 (purple) as well as between subsampling strategies, phylogenetic diversity-based sample (left,
779 dark grey) and stratified random sample (right, light grey). Median values (black midline)
780 indicated as well as the 95% highest posterior density (whiskers).

781 Figure S2. Host species temporal distribution of sampled North American avian influenza virus
782 PB2 gene segment sequences, 2005 – 2016. Proportions of represented host species are
783 compared between the phylogenetic diversity-based sample (PDA) and the stratified random
784 sample (stratified).

785 Figure S3. Geographic region temporal distribution of sampled North American avian influenza
786 virus PB2 gene segment sequences, 2005 – 2016. Proportions of represented regions are
787 compared between the phylogenetic diversity-based sample (PDA) and the stratified random
788 sample (stratified).

789 Figure S4. Heat map of supported viral transition rates among host species across avian influenza
790 virus gene segments and subtypes. Colored cells represent the magnitude of the transition rate
791 from the species in the first column (source) to the species in the second column (sink). White
792 cells were transition rates that were not supported (Bayes factor < 100). Results from both
793 subsampling strategies (phylogenetic diversity-based sample (PDA) and stratified random
794 sample (stratified)) are presented for comparison.

795 Figure S5. Discrete trait diffusion models of North American avian influenza using a stratified
796 random sample of genetic sequences. Host models (left) are presented for combined internal
797 gene segment (A), hemagglutinin gene subtype (B), and neuraminidase gene subtype (C) models.
798 Source host species on the left of the chord diagrams contribute viral diversity to sink host
799 species on the right. The magnitude of the viral transition rate is proportional to the width of the
800 band, and statistically supported rates darkened. Bands are colored by the host order of the
801 source species (Charadriiformes – red; Anseriformes – blue). Similarly, geographic models
802 (right) are summarized for combined internal gene segment (D), hemagglutinin gene subtype (E),
803 and neuraminidase gene subtype (F) models. Arrow width is proportional to the magnitude of the
804 transition rate, and only statistically supported rates are displayed. (AK – Alaska, AB – Alberta,
805 BC – British Columbia, GT – Guatemala, MW – Midwest, NB – New Brunswick, NE –
806 Northeast, NL – Newfoundland and Labrador, NRP – Northern Rockies and Plains, NS – Nova
807 Scotia, NW – Northwest, OV – Ohio Valley, PE – Prince Edward Island, QC – Quebec, S –
808 South, SE – Southeast, SON – Sonora, SW – Southwest, W – West)

809 Figure S6. Heat map of supported viral transition rates among geographic regions across avian
810 influenza virus gene segments and subtypes. Colored cells represent the magnitude of the
811 transition rate from the region in the first column (source) to the region in the second column
812 (sink). White cells were transition rates that were not supported (Bayes factor < 100). Results
813 from both subsampling strategies (phylogenetic diversity-based sample (PDA) and stratified
814 random sample (stratified)) are presented for comparison.

815 Table S1. Demographic characteristics of 303 wild bird surveillance samples with newly
816 sequenced avian influenza isolates, 2003 – 2016.

817 Table S2. Evolutionary parameters of avian influenza virus gene segments collected from North
818 American wild birds between 1970 and 2016. Datasets were sampled so as to maintain the total
819 phylogenetic diversity of the original publicly available sequence sample.

820 Table S3. Host and regional distribution of phylogenetic diversity-based subsample of influenza
821 virus gene segments isolated from North American wild birds.

822 Table S4. Host and regional distribution of stratified subsample of influenza virus gene segments
823 isolated from North American wild birds.

824 Tables S5 – S7. Host species transition rate matrix from combined internal gene model (Table
825 S5), combined hemagglutinin subtype model (Table S6), and combined neuraminidase subtype
826 model (Table S7). Median rates and 95% highest posterior density intervals are displayed for
827 both subsampling strategies. Rates colored in blue are statistically supported (Bayes factor >
828 100). (ABD – American black duck, BUF – bufflehead, BWT – blue-winged teal, CAN –
829 Canada goose, CIN – cinnamon teal, EMP – emperor goose, GAD – gadwall, GWF – greater
830 white-fronted goose, GWG – glaucous-winged gull, GWT – green-winged teal, LAU – laughing
831 gull, MAL – mallard, PIN – northern pintail, RED – redhead, RKN – red knot, RND – ring-
832 necked duck, RUD – ruddy turnstone, SHO – northern shoveler, SND – sanderling, SNO – snow
833 goose, WIG – American wigeon).

834 Tables S8 – 10. Geographic region transition rate matrix from combined internal gene model
835 (Table S8), combined hemagglutinin subtype model (Table S9), and combined neuraminidase
836 subtype model (Table S10). Median rates and 95% highest posterior density intervals are
837 displayed for both subsampling strategies. Rates colored in blue are statistically supported
838 (Bayes factor > 100). (AK – Alaska, ALB – Alberta, BCO – British Columbia, GUA –
839 Guatemala, MW – Midwest, NBR – New Brunswick, NE – Northeast, NFL – Newfoundland and

840 Labrador, RP – Northern Rockies and Plains, NSC – Nova Scotia, NW – Northwest, OV – Ohio
841 Valley, PEI – Prince Edward Island, QUE – Quebec, S – South, SE – Southeast, SON – Sonora,
842 SW – Southwest, W – West)
843 Table S11. Names and GenBank accession numbers of 303 newly sequenced AIV nucleotide
844 sequences.

Figure 1

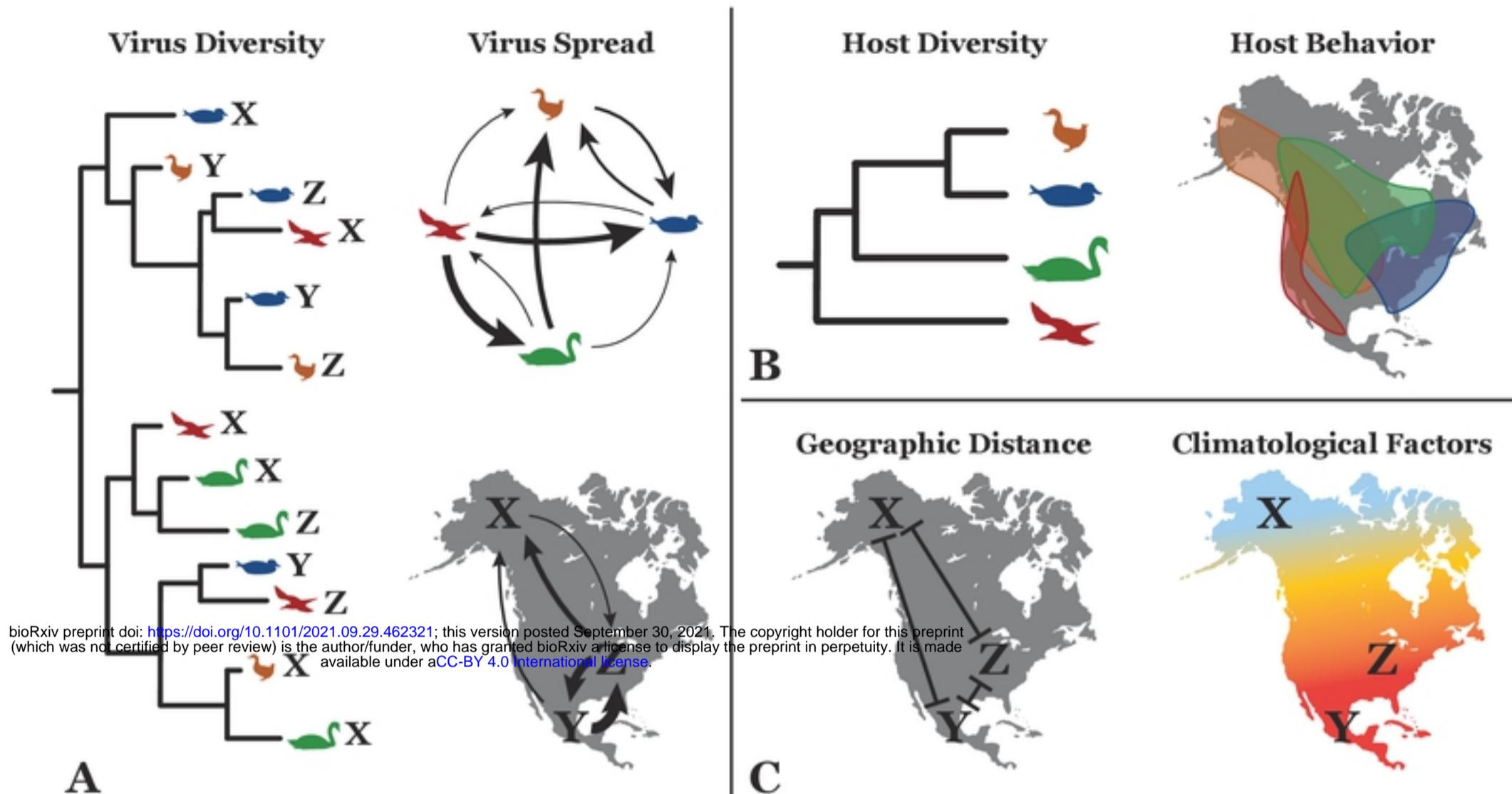


Figure 1

Figure 2

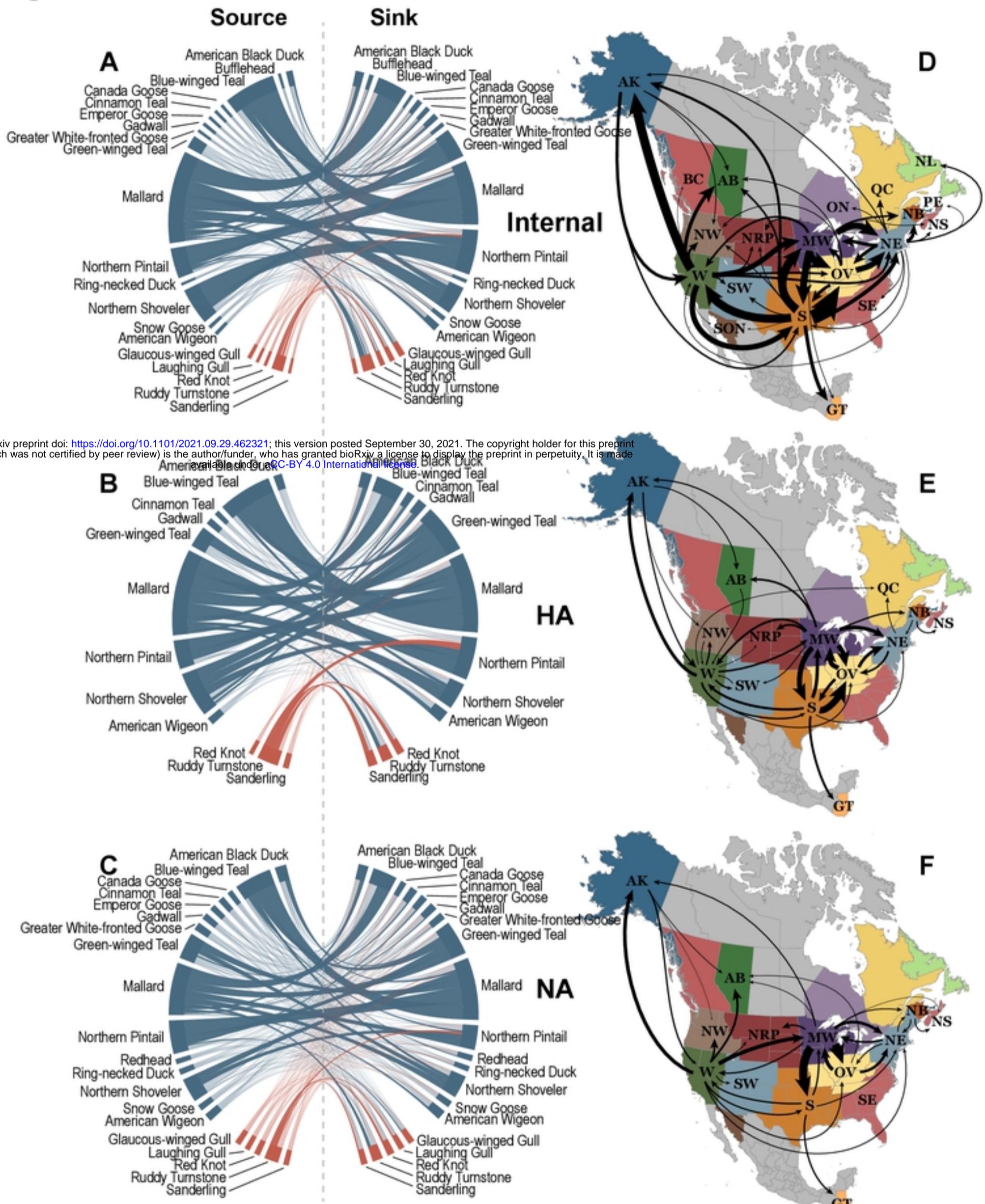


Figure2

Figure 3

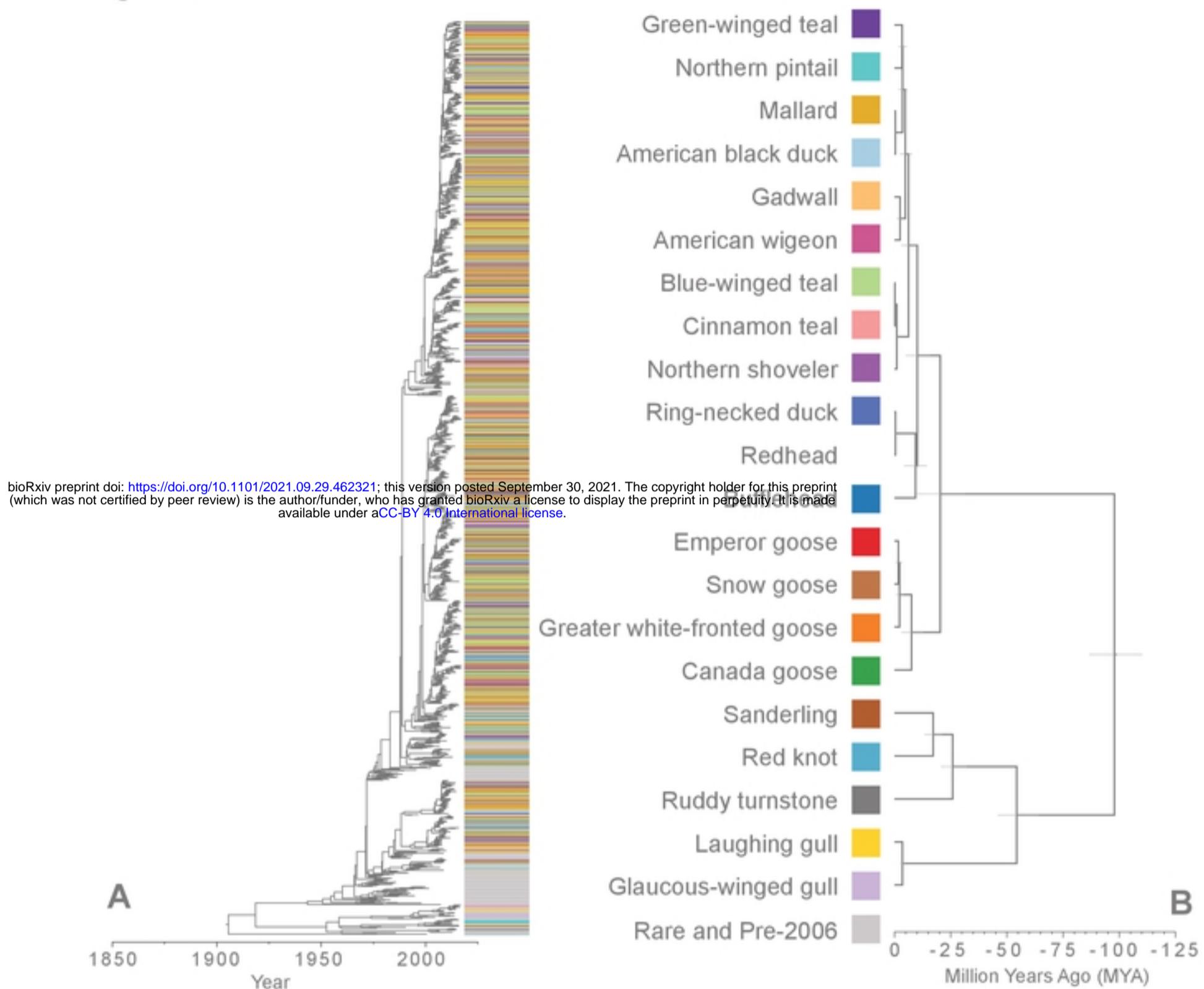


Figure3

Figure 4

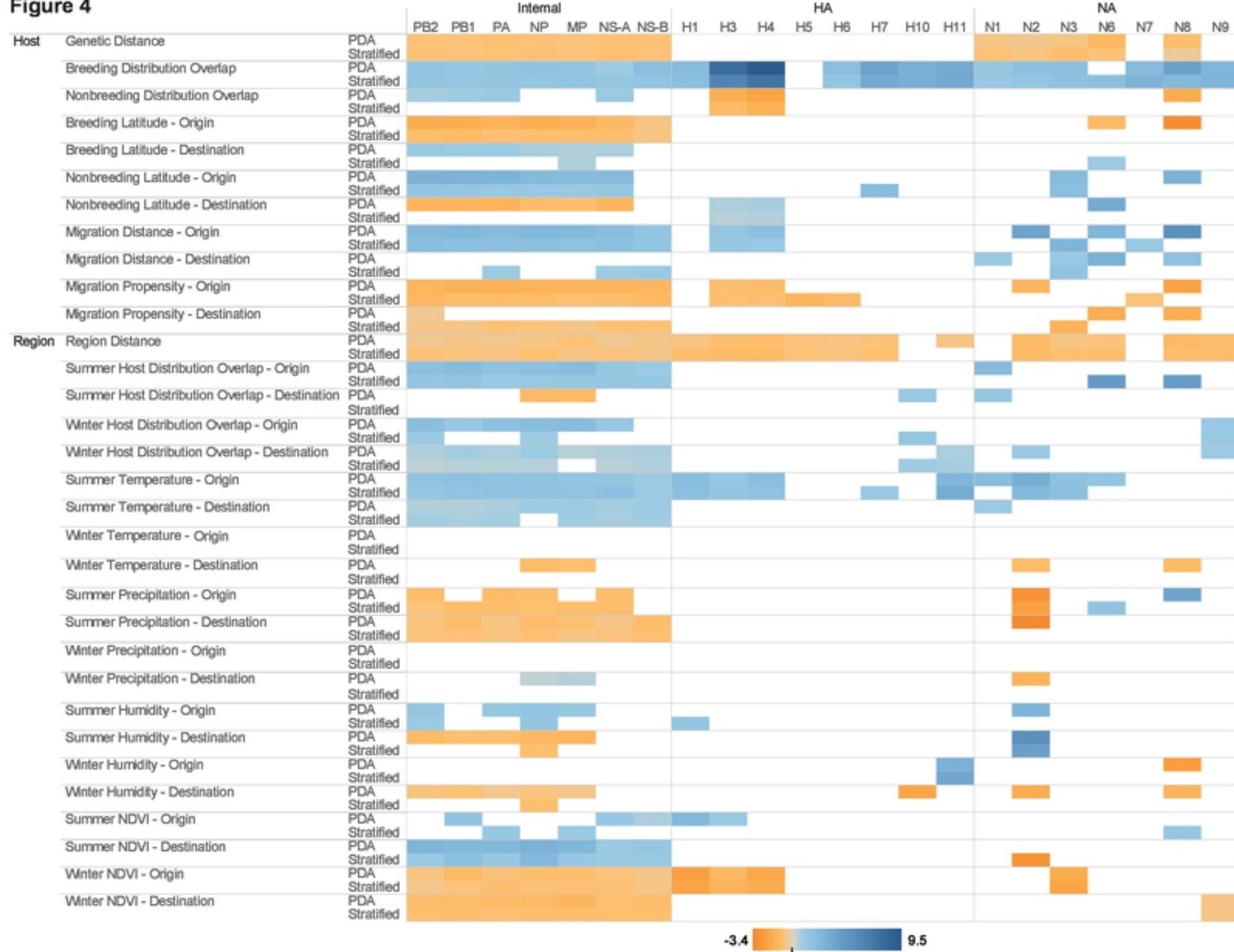


Figure4