

**Population Genomic Analyses Separate Historic Translocations from
Contemporary Gene Flow in Arkansas White-tailed Deer (*Odocoileus
virginianus*)**

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24 **ABSTRACT**

Approximately 100 years ago, hunter-harvest eliminated white-tailed deer (WTD; *Odocoileus*
26 *virginianus*) in eastern North America, which subsequently served as a catalyst for wildlife
management as a national priority. An extensive stock-replenishment effort soon followed, with
28 WTD broadly translocated among states as a means of reestablishment. Now, contemporary
issues focus on reverberations from a global (and fatal) epizootic disease in Cervidae (chronic
30 wasting disease, CWD). These cumulative impacts have effectively obscured the traditional
signals of post-translocation gene flow and dispersal in North American WTD. To develop
32 baseline data for its adjudication, we applied cutting-edge molecular and biogeographic tools to
process 1,143 WTD sampled state-wide in AR, with 54,102 single nucleotide polymorphisms
34 (SNPs) derived via reduced-representation genomic sequencing. We then employed Simpson's
diversity index to visualize landscape genetic patterns previously obscured by extensive
36 translocations, and this allowed us to summarize multidimensional ancestry assignments and
identify spatio-genetic transitions. We then sub-sampled transects and tested clinal patterns
38 across loci for concordance and/or coincidence. Two salient results emerged: (A) Genetic echoes
from historic translocations are widely apparent; and (B) Geographic filters (major rivers; urban
40 centers; highways) now act as inflection points for the distribution of more contemporary
ancestry. These results, in synergy, yielded a state-wide assessment of how historic
42 translocations, as well as ongoing processes, have acted to dictate contemporary population
structure of Arkansas WTD. In addition, the analytical framework employed herein effectively
44 deciphered the extant/historic drivers of WTD distribution in AR. It is also applicable for other
biodiversity elements with demographic histories equally as complex.

46

1 | INTRODUCTION

48 Distribution and abundance are key natural history attributes that provide a foundation for
organismal ecology (Andrewartha & Birch, 1956; Kissling et al., 2018). Each is geographically
50 and hierarchically structured, often across several spatial scales, and in response to a non-random
distribution of resources and refugia (Turner, 1989). Species distributions and abundances are
52 increasingly impacted by habitat fragmentation, over-exploitation, and translocation in the
Anthropocene (Baker et al., 2017; Corlett, 2015), with the functional integrity of these attributes
54 being severely challenged. Hunter-harvest, an additional anthropogenic impact, also exerts a
relatively consistent global impact on biodiversity (Darimont et al., 2009). Given the manner by
56 which abundances and distributions have been so impacted, other attributes such as dispersal and
population connectivity have subsequently emerged as focal points for contemporary wildlife
58 management, (Crooks & Sanjayan, 2006; Cushman, Elliot, Macdonald, & Loveridge, 2016).
Here we focus on these latter attributes as we evaluate historic and contemporary population
60 structure in a wild Arkansas (AR) ungulate (white-tailed deer, WTD; *Odocoileus virginianus*).

62 1.1 | Dispersal, connectivity, and population structure

Dispersal and connectivity have been traditionally assayed for management purposes using direct
64 methods such as radio- and satellite-tracking (Kays, Crofoot, Jetz, & Wikelski, 2015), yet both
have deficiencies such as low sample-sizes and a perspective that must extrapolate from
66 individuals to populations (Katzner & Arlettaz, 2020). An indirect approach, on the other hand,
relies instead upon gene flow (i.e., movements, demographics) and genetic drift (i.e.,
68 heterozygosity, effective population size) to quantify population-level movement ecology
captured over many generations (Bossart & Prowell, 1998; Comte & Olden, 2018). Landscape

70 genetics, for example (Richardson, Brady, Wang, & Spear, 2016), quantifies movement patterns
by evaluating the spatial structure inherent to genetic diversity (as mediated by dispersal and
72 gene flow), and does so for greater numbers at a fraction of the per-individual cost (Picard et al.,
2017; van Rees, Reed, Wilson, Underwood, & Sonsthagen, 2018; Wang & Shaffer, 2017).

74 We now recognize that genotypes within a species (i.e. gene pool) vary across
landscapes, often coalescing as discretely recognizable sub-populations (i.e., intra-specific
76 population structure driven by mutation, selection, gene flow, genetic drift), and visualized/
interpreted at varying degrees both temporally and spatially (Barton & Clark, 1990; Slatkin,
78 1989). They span from the afore-mentioned sub-populations through continuously decreasing
gradients of genetic similarity that extend over geographic or environmental distance (i.e.,
80 isolation by distance: Avise 1992; Bohonak 1999; Bradburd et al. 2018). Structure can be
ascertained by sampling individuals across appropriate spatial scales, relative to the dispersal
82 kernel of the organism (Nathan, Klein, Robledo-Arnuncio, & Revilla, 2012). It can then be
employed to test hypotheses about the likely causes of observed genetic patterns (Bradburd,
84 Ralph, & Coop, 2016; Miles, Rivkin, Johnson, Munshi-South, & Verrelli, 2019). However, gene
flow and genetic drift are often conflated, and their deconstruction is an important aspect when
86 attempting to clarify how population genetic structure is driven.

Patterns of genetic diversity are also impacted by multiple extrinsic and intrinsic factors.
88 For WTD, those extrinsic may include: Rivers, interstate highways, large tracks of forested
habitat (Robinson, Samuel, Lopez, & Shelton, 2012); agricultural land use, climate-related
90 factors (Brinkman, Deperno, Jenks, Haroldson, & Osborn, 2005); and landscape connectivity
(Koen, Tosa, Nielsen, & Schaubert, 2017). Intrinsic factors, on the other hand, may reflect:
92 Population density (Lutz, Diefenbach, & Rosenberry, 2015); age structure/ sex ratio (Long,

Diefenbach, Rosenberry, & Wallingford, 2008); and social hierarchy (Nixon & Mankin, 2016).

94 Factors that traditionally shape dispersal and genetic diversity within/ across regions can
difficult to quantify in that anthropogenic actions such as translocation or trafficking can obscure
96 existing patterns (Brown, Hull, Updike, Fain, & Ernest, 2009; Shephard, Ogden, Tryjanowski,
Olsson, & Galbusera, 2013). This is particularly true for WTD, as it is one of the most
98 recreationally important animal species in North America (Knoche & Lupi, 2012), with
populations intensely impacted by both hunter harvest and game management (Waller &
100 Alverson, 1997; Wolverton, Kennedy, & Cornelius, 2007). For example, at the beginning of the
20th century, WTD and other heavily hunted species (e.g., wild turkey) saw heavy declines and
102 widespread extirpations. In a census of the north-central United States, Leopold (1931) noted "...
some deer" were still extant in southern Missouri at this time, and this dovetails with WTD
104 numbers estimated in Arkansas (~500 scattered across isolated refugia; Holder, 1951).
Subsequent AR efforts to bolster resident numbers and re-populate depleted areas involved
106 translocations within-state, as well as importations from out-of-state. Although successful, a
result of these efforts is that apparent genetic patterns are likely to be strongly reflective of
108 artificial, rather than natural, movements.

A first step in designating factors that have shaped WTD population structure and
110 dispersal is to estimate that genetic component that remains within AR WTD genomes as a
residual of historic translocations and subsequent genetic drift. Perhaps the most pressing need to
112 understand WTD dispersal is the impact these data have with regard to the potential containment
and mitigation of a widespread and fatal neurodegenerative disease of cervids (chronic wasting
114 disease; CWD), that has now become a panzootic (Williams and Young 1980; Escobar et al.
2019; Mawdsley 2020). Thus, efforts to contain and mitigate its spread are paramount for

116 wildlife management, not only in North America but also globally (Leiss et al., 2017).

118 **1.2 | Dispersal, connectivity, and management**

An understanding of the manner by which WTD disperse across the landscape has clear
120 management implications. Its landscape movements are many and varied, as driven by habitat
quality, climate, and anthropogenic benefits. Region-specific patterns are needed so as to
122 develop broader generalizations regarding species-specific movement ecology (Brinkman et al.,
2005).

124 The goal of our study was to ascertain if signatures of historic translocations are apparent
in, and have contributed to, the genetic diversity and structure of Arkansas WTD, and
126 furthermore, if they can indeed be parsed from ongoing gene flow and genetic drift. To do so, we
surveyed a broad array of nuclear genomic markers using ddRAD sequencing (Peterson et al.,
128 2012). Our first objective was to characterize respective patterns of anthropogenic translocation
and natural re-colonization via refugial populations, and secondarily to seek evidence for
130 geographic barriers throughout the state that seemingly prevent or actively filter WTD dispersal.
However, we hypothesized that the former situation would obscure the latter, in that long-range
132 anthropogenically-mediated displacement of individuals violates methodological assumptions
that stipulate gene flow as occurring in a spatially consistent manner (Bradburd & Ralph, 2019).

134 To address this, we repurposed existing formulas that summarized ancestry assignments
by reducing their dimensionality, and mitigated methodological artefacts due to translocation
136 (Simpson, 1949). Our result was an interpolated ‘surface’ representing putative intraspecific
suture zones. We also wished to define the respective roles played by stochastic and
138 deterministic processes in generating these zones, particularly given historic population

fluctuations and the internal/ external translocations that conflated the demography of AR WTD.

140 To do so, we borrowed components of clinal variation theory so as to hypothesize the manner by
which individual loci should transition across these spaces, relative to a genome-wide average
142 (Barton, 1983; Barton & Hewitt, 1985; Endler, 1973; Hewitt, 2001; Polechová & Barton, 2011;
Slatkin, 1973).

144 Although clinal variation is often taken as evidence for selection, genetic drift in concert
with spatially variable gene flow can generate patterns in individual loci that mimic those seen in
146 adaptive clines (Vasemägi, 2006). With drift operating alone, allele frequencies at each locus
may wander ‘upward’ or ‘downward’ across space as a function of the initial allele frequency.
148 Range expansion or dissemination from refugia can also yield a type of ‘rolling’ founder effect
that can mirror a clinal pattern (Excoffier, Foll, & Petit, 2009; Hallatschek & Nelson, 2008;
150 Hewitt, 2000; Keller et al., 2013). Given this, we might predict that multi-locus patterns at
intraspecific suture zones generated solely as a result of genetic drift in expanding populations
152 will be dominated by stochastic directional change, with each drifting either up or down with
respect to the genome-wide average (Santangelo, Johnson, & Ness, 2018). On the other hand, a
154 strong barrier to movement would yield a discontinuity in the rate of this change across space
(Barton, 2008; Nagylaki, 1976; Slatkin, 1973). The existence of a barrier (either impacting
156 dispersal or as a strong fitness differential) thus implies the presence of an inflection point that
would induce a sigmoidal change in locus-specific ancestries (the “width” of this cline is the
158 inverse of the slope at the inflection point; Slatkin 1973; Endler 1977; Fitzpatrick 2013).

Given these predictions, we summarized locus-wise patterns using two clinal parameters:

160 α , which describes the direction of genetic change (i.e. directionally), and β , which indicates the
rate of change, or ‘width’ of a cline. We examined the manner by which these two parameters

162 varied, then developed hypotheses regarding how those processes impacted our observed
population structure. We then considered the evolutionary implications, and limitations, of these
164 results in the context of WTD management.

166 **2 | METHODS**

2.1 | Sampling and data collection

168 During 2016-2019, 1,720 tissues were collected by the Arkansas Game and Fish Commission
(AGFC), representing all 75 Arkansas counties. A combination of targeted sampling, road-kill
170 surveys, and a voluntary state-wide CWD testing program were deployed (see Douglas et al.,
2020). Age and sex were collected where possible, with the former estimated by tooth
172 development and wear (Severinghaus, 1949). Data for an additional 30 samples were also
attained from Wisconsin, as a means to test for signals of historically recorded translocation
174 efforts involving Wisconsin stock (Holder, 1951). From these, a subset of 1,208 samples were
chosen for sequencing.

176 We homogenized tongue or ear tissue (stored at -20°C) and extracted genomic DNA
using QIAamp Fast Tissue kits (Qiagen, Inc), with verification via gel electrophoresis (2%
178 agarose). Samples with sufficient yields of high molecular weight DNA (>200ng minimum)
were then enzymatically fragmented via incubation at 37°C, using high-fidelity *NsiI* and *MspI*
180 restriction enzymes (New England Biolabs, Inc.), following enzyme and size selection
optimization using *in silico* digests (Chafin, Martin, Mussmann, Douglas, & Douglas, 2018) of
182 several available reference genomes hosted by NCBI: *Odocoileus virginianus*
(GCA_002102435.1), *Capreolus capreolus* (GCA_000751575.1), and *Capra hircus*
184 (GCF_001704415.1).

Digests were purified using Ampure XP beads (Beckman-Coulter, Inc.) and standardized
186 to 100ng per sample. Unique inline barcodes (Peterson et al., 2012) were then ligated using T4
DNA Ligase (following manufacturer protocols; New England Biolabs, Inc.). Samples were then
188 multiplexed (N=48) prior to automated size selection at 300-450bp using a Pippin Prep (Sage
Sciences). Adapter extension was performed over 12 PCR cycles using TruSeq-compatible
190 indexed primers (Illumina, Inc.) and Phusion high-fidelity *taq* polymerase (New England
Biolabs, Inc.) Additional quality controls (e.g., qPCR and fragment analysis) were performed on
192 final libraries prior to 1x100 single-end sequencing on the Illumina HiSeq 4000 (Genomics and
Cell Characterization Facility, University of Oregon/Eugene), with a total of N=96 samples
194 pooled per lane.

Raw reads were demultiplexed using the pyRAD pipeline (Eaton, 2014), and those with
196 barcode mismatches were discarded. Demultiplexed reads were further filtered by removing
those having >4 nucleotides below a quality threshold of 99% accuracy. Reads were then
198 clustered into putative loci within-individuals, allowing for a maximum distance threshold of
15%. This was done using the VSEARCH algorithm (Rognes, Flouri, Nichols, Quince, & Mahé,
200 2016) as implemented in pyRAD, so as to remove read clusters with 3+ indels, >5 ambiguous
consensus nucleotides, or a coverage <20X or >500X. Putative homologs were identified using
202 among-individual clustering with the same parameters, and additionally removing any locus
having >2 alleles per individual, >70% heterozygosity for any polymorphic site, >10
204 heterozygous sites, or <50% individual recovery (see github.com/tkchafin/scripts for post-
processing and file formatting scripts).

206

2.2 | Derivation of population structure

208 We first sub-sampled the dataset to one SNP per locus and excluded those with a minor allele
count <2. We then inferred population structure (ADMIXTURE: Alexander et al., 2009) with
210 parallel processing (ADMIXPIPE: Musmann et al., 2020). Model selection (i.e. for K , the number
of populations) followed a cross-validation approach with results aggregated from 20
212 independent replicates (CLUMPAK: Kopelman et al., 2015).

Individual-level ADMIXTURE results were summarized as a ‘surface’ with spatial
214 discontinuities represented as interpolated assignment probabilities. Here, we constructed state-
wide rasters, as representing per-pixel probabilities or ‘ancestry proportions,’ using Empirical
216 Bayesian Kriging (EBK: ARCMAP 10.7.1, Esri, Inc.). Probability surfaces were then summarized
as evenness and diversity of ancestries in a given cell using Simpson’s index (Simpson, 1949)
218 (where K =number of statewide sub-populations). Our use of the diversity index was based on a
straightforward prediction: Areas representing spatial transitions between populations will have a
220 correspondingly low certainty of assignment to a given sub-population ancestry. Likewise, those
with low inter-population exchange will be comprised of genetically similar individuals assigned
222 with high probability to the endemic ancestry. Thus, intraspecific suture zones represent a
marked transition from one population to another, as identified by site-wise diversity in
224 assignment probabilities (i.e., “ancestry diversity”).

We expect spatial variation in ancestry diversity to be inversely proportional to true rates
226 of gene flow, in that this quantity (as well as the ancestry proportions from which it is computed)
are a product of gene flow averaged over many generations. Of note is the fact that the method
228 only examines local ancestry probabilities and will not be dominated by translocation-related
artefacts (as are methods based on interpolated pairwise genetic distances or F_{ST}). Patterns based
230 on Simpson’s diversity were contrasted with those inferred using a form of 2D-stepping stone

232 model (EEMS; Petkova et al. 2015), which was run with 2 million MCMC iterations (1 million
as burn-in), and sampled every 1,000 iterations [following parameter sweeps that tuned MCMC
acceptance rates to fall between 20% and 50% (Roberts, Gelman, & Gilks, 1997)].

234

2.3 | Estimating clinal parameters

236 We examined the nature of intraspecific suture zones by examining how individual loci
transitioned across these regions, relative to the genome-wide average. To do so, we defined
238 eight transects across putative suture zones, sampling 32-73 individuals per transect ($\bar{x} = 55.38$).
Individuals were chosen to represent each sub-population using a probability threshold applied to
240 ADMIXTURE results. Loci were filtered to remove all SNPs with missing data in >50% of
individuals, and further restricted with regard to computational time by retaining only those loci
242 with a sufficient allele frequency differential [computed as $\delta > 0.50$; (Gregorius & Roberds,
1986)]. Locus-wise clinal patterns were then inferred using a Bayesian method developed
244 originally for hybrid zones (Gompert & Buerkle, 2011, 2012). Open source Python code for
filtering SNP matrices and generating necessary input are available at:
246 (github.com/tkachafin/scripts/phylic2introgress.pl and [phylic2bgc.pl](https://github.com/tkachafin/scripts/phylic2bgc.pl)).

Analyses were performed for each transect across 4 replicates, each using 1 million
248 MCMC iterations, discarding the first 500,000 as burn-in, with output thinned to every 500
iterations. Results were summarized by visualizing a 2-D density of cline shape parameters.
250 These are: α (=cline center) that describes an increase ($\alpha > 0$) or decrease ($\alpha < 0$) in the
probability of locus-specific ancestry from a parental population; and β (=cline rate) that defines
252 the rate of transition in probabilities of locus-specific ancestries having either steep ($\beta > 0$) or
wide ($\beta < 0$) shapes (Gompert, Parchman, & Buerkle, 2012). In this context, a locus which does

254 not deviate from the genome-wide pattern would have $\alpha=\beta=0$. Deviation in a directional manner
(i.e., an increase or decrease of one ancestry over another) is described by α , whereas deviation
256 in the rate of ancestry change around an inflection point (i.e., sigmoidal) is described by β .
Statistical outliers were designated using the method of Gompert and Buerkle (2011). BGC
258 results were parsed and visualized using the ClinePlotR R package (Martin et al. 2020a,b)

260 **2.4 | Relative dispersal by age and sex**

Of particular interest in wildlife management is the backwards inference of geographic
262 positioning from genotypes—that is, the geolocation of ‘origination’ points for sampled animals.
This could be used, for example, to ascertain the geographic origin of poached individuals, or to
264 estimate post-natal dispersal. To this end, we used the novel, deep-learning method LOCATOR
(Battey, Ralph, & Kern, 2020) to predict the geographic origin of samples without relying upon
266 explicit assumptions about population genetic processes underlying spatial genetic differentiation
(Bradburd & Ralph, 2019). This analysis was performed iteratively across each individual, using
268 the remaining samples to train the LOCATOR classifier, with 100 bootstrap pseudo-replicates to
assess variance in geolocation. Given computational constraints, we performed the analysis using
270 a subset of 5000 SNPs having a minor allele frequency >10%.

We estimated relative dispersal distances as the Euclidean distance between sampled
272 localities and the centroid of predicted coordinates, under the assumption that the distance
between predicted and collection locations is the result of lifetime dispersal, at least for samples
274 for which geolocation variance is low among pseudo-replicates. These results were then
partitioned by age, sex and CWD-status.

276 Our second approach examined the decay in genetic relatedness as a function of distance

from each individual, measured as a Prevosti distance (R-package poppr: Kamvar et al., 2014).

278 Here, the assumption is that recently dispersed individuals will be, on average, more genetically
dissimilar from resident individuals, whereas resident individuals having an appreciable
280 reproductive output will be less so. These calculations were limited to individuals that had
neighboring samples within a 5km radius, thus implicitly restricting the analysis to high-density
282 sampling regions. We note, however, that the traditional aging method employed for AR WTD
(Severinghaus 1949) seemingly has reduced accuracy in older deer, potentially suggesting
284 caution in the interpretation of results (Cook & Hart, 1979; Gee, Holman, Causey, Rossi, &
Armstrong, 2002; Mitchell & Smith, 1991).

286

3 | RESULTS

288 3.1 | Data processing

Our raw data represented N=1,143 samples, including N=29 from Wisconsin (Table S1). We
290 removed N=83 that had missing metadata, discrepancies with coordinates, or <50% of loci
present. Assembly in pyRAD yielded an average of 25,584 loci per sample ($\sigma=8,639$). After
292 removing loci present in <50% of samples and excluding those containing potential paralogs
(e.g. excessive heterozygosity or >2 alleles per locus), our final dataset contained 35,420 loci,
294 from which 2,655,584 SNPs were catalogued. Of these, 54,102 were excluded as singletons. To
limit signal redundancy, we then condensed the data to one SNP per locus, yielded a final matrix
296 of 35,099 SNPs for analyses of population structure.

298 3.2 | Population structure and ‘ancestry surfaces’

Cross-validation, performed on N=20 replicates each for subpopulation model ($K=1-20$),
300 revealed the optimal number of clusters as $K=8$. Spatial orientation of these samples (Fig. 1)
provided a geographic definition, with some subpopulations qualitatively defined by apparent
302 landscape features, such as the Arkansas River Valley as the southern extent of subpopulations
 $k=3$ and $k=6$.

304 Two ancestries ($k1$ and $k8$) largely dominated south of the Arkansas River, bounded by
Interstate 30 to the north and the Ouachita River to the south (Figs. 1-2), each of which supports
306 the argument that genetic structure is defined by large geographic barriers. The southwestern
portion of the state has two ancestral assignments ($k1$ and $k3$), with the latter having mixed
308 representation in the north-central section (potentially an artefact of weak differentiation rather
than true shared ancestry). The southeastern section is dominated by a single gene pool ($k8$),
310 which coincidentally subsumed all Wisconsin samples, a strong signature of genetic variability
as a residual of historic translocations.

312 A greater amount of endemic structure occurred in the Ozark Mountains, north of the
Arkansas River, where six sub-populations were evident. The most broadly distributed ($k5$) was
314 to the east in the Mississippi alluvial plains, extending westward across the mainstem of the
White River then northward towards the confluence of the Black and White rivers, where it
316 grades into several distinct yet loosely defined sub-populations (Figs. 1-2). The northwestern
corner of the state was the most heterogeneous, with four primarily endemic gene pools ($k=2,3,4$
318 and 7; Fig. 2). The northern-most of these was approximately bounded by the White River (Fig.
2), and graded westward into an area of high apparent admixture (Fig. 1). The remaining
320 northwestern region was defined by several gene pools showing considerable admixture and

spatially weak transitions, suggesting reduced gene flow but with geographic and/ or
322 environmental boundaries reasonably porous.

Effective migration surfaces (EEMS) failed to capture any ascertainable pattern relating
324 to spatially defined population structure (Fig. S1). Geographic breaks separating sub-populations
(=suture zones) were captured instead by reducing the dimensionality of interpolated assignment
326 probabilities as a continuous Simpson's diversity index (Fig. 3). This, in turn, reflects a
dependence on homogeneity of local assignments, rather than global patterns compounded by
328 long-distance transplants.

330 **3.3 | Intraspecific genomic clines**

Genomic clines varied substantially among transects (Figs. 4, S2). Most inter-population
332 comparisons within northwest Arkansas, to include $k2 \times k3$ (both eastern and southern transition
zones), $k2 \times k6$, and $k4 \times k7$, indicated variation primarily restricted to cline centers (α), with
334 cline steepness (β) at a minimum. The variation in locus-wise pattern for these cases (hereafter
termed " α -dominant"), indicated a directional change in the representation of reference
336 populations across the transect, but without a noticeable 'inflection' point, as implied by non-
zero cline rates (β).

338 Remaining comparisons, including one additional transect from northwest Arkansas ($k3 \times$
 $k4$), primarily reflected variation in cline rate (β), in that loci varied most prominently with
340 regard to steepness/width of transition around an inflection point respective to genome-wide
ancestry. Although two transects showed minor exception to this pattern (i.e., $k3 \times k6$ varied
342 along both parameters; and $k4 \times k7$ showed minimal variation in either), the contrasting variation

between α -dominant versus β -dominant transects suggests that different processes underly
344 ancestry transitions.

346 **3.4 | Estimating dispersal using geolocation analysis**

Individuals from densely sampled regions could be assigned to geographic origin using the
348 ‘deep-learning’ approach, with CWD-positive individuals assigned with a mean bootstrap
distance from centroid prediction generally <15km (Fig. S3). However, we did find assignment
350 error (e.g., among bootstraps) was elevated in low-density sampling regions (Figs. 5, S4), which
resulted in higher estimated individual dispersal distances (Fig. S4A, B). Given that variance in
352 dispersal estimates dropped considerably below ~25km (Fig. S4C), a conservative threshold of
10km was chosen and all individuals having a mean bootstrap-centroid distance above that were
354 removed for the purposes of dispersal estimates. After filtering, N=110 samples remained (Fig.
5A). A higher error threshold (i.e., 20km) allowed a greater number of total samples to be
356 incorporated (N=264; Fig. 5B), with several collected as ‘roadkill’ appearing as long-distance
transfers. Although these results represent low-precision assignments, they do underscore the
358 capacity of the method with regard to the identification of transported individuals (e.g., as
poached or illegally dumped deer, or carcasses transported across state lines or regional
360 management zones).

Geo-located results for those individuals passing a strict error filter demonstrated a
362 dispersal distance for males approximately doubled that of females across all age classes
(statistically significant only for the Y2-2.5 class due to low sample sizes; Fig. 6). This pattern
364 was established as early as the Y1-1.5 group, indicating apparent male dispersal by that age.

Smaller dispersal distances were found for fawns across both sexes (Fig. 6), again corroborating
366 *a priori* biological expectations.

Patterns of genetic dissimilarity also showed an age x sex effect, with greater genetic
368 dissimilarity for neighboring Y0-1 males than females, and with a shift towards reduced
dissimilarity in males >5 (Fig. S5). This again supports that male deer in Arkansas have
370 dispersed by the Y1-1.5 age class. These results potentially reflect age-biased reproduction as
well. Males contributed disproportionately to their local gene pools by age 5 (i.e., producing
372 offspring with resident females), thereby creating a pattern of lower genetic dissimilarity among
neighboring individuals, regardless of distance.

374

4 | DISCUSSION

376 4.1 | Genetic footprints of historic management

The prolonged history of WTD hunter-harvest, and subsequent long-range translocations into
378 Arkansas and the surrounding region (Ellsworth et al., 1994; Holder, 1951), provide a sideboard
to our study in that artificial long-distance movements such as these violate the assumptions
380 inherent with many spatially-explicit methods. However, we found estimates of ancestry
diversity and probability surfaces to be qualitatively robust in that they firmly recapitulated the
382 record of historic translocations (Holder, 1951). This, in turn, necessitates an explanation of
historic context.

384 In the early 20th century, following many decades of over-hunting, AR WTD declined to
<500 individuals (Holder, 1951). In response, Arkansas Game and Fish Commission (AGFC)
386 implemented an extensive restocking program (1941-1951) by establishing three primary sources
as its basis. The first was Howard County WTD farm (southwestern Arkansas; Fig. 7),

388 established from locally transplanted central Arkansas individuals (Wynn, 1943). It is now
located within the epicenter of population *k1* (Figs. 2, 7), with ancestry shared elsewhere in the
390 state, thus supporting it as a local translocation epicenter.

A second major source was the Sylamore District (Ozark Mountains; Wood, 1944;
392 Holder, 1951), where individuals were naturally abundant (Fig. S7). Individuals from this region
have a consistently higher probability of assignment to *k3* (Figs. 2, 7), where records indicate
394 ~81% of repopulated individuals in the Gulf Coastal Plain originated from the Sylamore cluster
(Holder, 1951; Karlin, Heidt, & Sugg, 1989; Wood, 1944). Our analyses are in agreement, in that
396 many individuals in southwestern Arkansas (Figs. 1, 6) reflect a mixed assignment to the
“Sylamore” cluster. They also comprised ~36% of stocking efforts in the Mississippi Delta
398 region (Karlin et al., 1989).

Our results also indicate some mixed assignment of individuals to *k3*, although a more
400 widespread representation is found in *k5*. AGFC surveys (~1942-1945) indicate WTD as
relatively abundant in the southeastern Delta region (Figs. 7, S7), allegedly linked with re-
402 population efforts following the disastrous 1927 Mississippi flood. This event, coupled with
over-hunting, nearly extirpated WTD in the region, save small numbers sustained by local
404 sportsmen (Holder, 1951; Fig. S7). We hypothesize WTD in the Delta region largely descended
from those efforts, given the contemporary homogeneity of ancestry assignment for this region.

406 A third (extraneous) WTD source was the Sandhill Game Farm (Babcock, WI; Wood
1944). Records indicate that ~64% of releases into the Mississippi Delta region originated out-
408 of-state, the majority from Wisconsin (Holder, 1951; Karlin et al., 1989). Our Wisconsin samples
were unanimously assigned to a gene pool prominently represented in the southern Delta region
410 (*k8*; Fig. 2), firmly establishing its genetic legacy as extending from imported deer.

Mitochondrial haplotypes putatively originating from Wisconsin were also uncovered in
412 Missouri, Kentucky, and Mississippi (Budd, Berkman, Anderson, Koppelman, & Eggert, 2018;
DeYoung et al., 2003; Doerner et al., 2005).

414 All genetic ‘clusters’ that lacked spatial cohesion in our analyses can be connected to the
three major stocking sources involved in earlier restoration efforts (per reference to historic
416 records). The remaining sub-populations, primarily in the Ozarks (*k*2, 4, 6, and 7) may represent
natural re-colonization from refugial populations (Figs. 2, 7), an hypothesis supported by early
418 census data (Figs. S7, S8).

420 **4.2 | Landscape-drivers of contemporary population structure**

A primary focus in our study was the contemporary genetic structure of AR WTD, especially
422 with regard to the manner by which these data promote landscape resistance and potentially
constrain CWD infection (Hemming-Schroeder, Lo, Salazar, Puente, & Yan, 2018; Kelly et al.,
424 2014). Yet several prerequisites are apparent in this regard. For example, one question which is
apparent but previously constrained by technological limitations is the degree to which potential
426 patterns of genetic variability in WTD have been conflated by anthropogenically-mediated
translocations.

428 We addressed this issue by utilizing next-generation molecular techniques to derive
highly variable SNP markers. We also implemented advanced geospatial procedures that
430 visualized the spatial transitions inherent within WTD ancestry in such a way that translocation
histories were not a limiting factor. We did so by interpolating our assignment probabilities from
432 ADMIXTURE, then applying Simpson’s diversity index as a means of reducing the
dimensionality of these probabilities. We also examined locus-specific patterns within our

434 transitions so as to polarize stochastic versus deterministic processes.

Previous studies concluded that landscape genetic inferences were limited at best, due to
436 complex interactions between historic translocations and subsequent population growth (Leberg
et al. 1994; Leberg and Ellsworth 1999; Budd et al. 2018). However, many of these studies relied
438 upon (now) obsolescent molecular markers (e.g., mtDNA or reduced panels of microsatellite
DNA markers) that captured substantially less polymorphism than do next-generation methods
440 (Hodel et al., 2017; Jeffries et al., 2016; Lemopoulos et al., 2019). Subsequent studies at finer
spatial scales have supported the role of large-scale geomorphic configurations (e.g., rivers,
442 highways) as semipermeable barriers to WTD gene flow (Kelly et al., 2014; Locher et al., 2015;
Miller et al., 2020; Robinson et al., 2012), despite the potential complication caused by re-
444 stocking efforts, and in accordance with radio-telemetry data (Peterson et al., 2017).

Spatio-genetic patterns can still be informative with regards to landscape-level dispersal,
446 despite rapid transitions between historical and contemporary conditions (Epps & Keyghobadi,
2015) which might be expected to obfuscate relationships. For example, spatial genetic patterns
448 in invasive species are also attributable to large-scale environmental features, despite oft-reduced
levels of genetic diversity (Lopez, Hurwood, Dryden, & Fuller, 2014; Sacks, Brazeal, & Lewis,
450 2016; Zalewski, Piertney, Zalewska, & Lambin, 2009). The same can be said for populations
occupying landscapes defined by recent anthropogenic developments, such as large urban
452 centers, suggesting the potential for such patterns to rapidly emerge (Beninde et al., 2016;
Combs, Puckett, Richardson, Mims, & Munshi-South, 2018; Kimmig et al., 2020). In the case of
454 translocation, the magnitude of analytical artefacts are expected to be both scale-dependent, and
a function of the specific analytical assumptions. For example, classic tests of ‘isolation-by-
456 distance’ implicitly assume a negative relationship between geographic proximity and pairwise

patterns of genetic distance (Meirmans, 2012; Rousset, 1997). Here, translocations are
458 demonstrably inconsistent with this expectation.

The assignment method used in our study yielded patterns of genetic similarity that
460 reflected translocations as depicted in historic records (Fig. 7). We sought to effectively
'remove' this artificial signal so as to more appropriately expose landscape features that could
462 potentially modulate deer dispersal. Our approach (i.e., reducing dimensionality of assignment
probabilities) produces relatively straightforward predictions about the ensuing metric: Areas
464 with an elevated flux of individuals should have elevated homogeneity with regard to
interpolated ancestry assignment (i.e., ADMIXTURE ancestry proportions). By the same logic,
466 regions that reflect transitions in ancestry proportions would also demonstrate reduced
homogeneity. Although spatial assignments can also be vulnerable to artefacts, such as the over-
468 fitting of discrete clusters within otherwise continuous populations (Bradburd et al., 2017), they
effectively identify linear barriers to gene flow (Blair et al., 2012). Coincidentally, our approach
470 to dimensionality-reduction also revealed numerous linear subdivisions that aligned with major
landscape barriers, such as Arkansas rivers (Fig. 3). Other putative transitions approximately
472 corresponded with large urban centers.

474 **4.3 | Separating stochastic versus deterministic processes in clinal patterns**

It is difficult to disentangle contemporary demographic processes (versus analytical
476 idiosyncrasies) in the formation of these patterns. As a means of clarification, we generated
multi-locus genomic patterns (Epps & Keyghobadi, 2015) under the expectation that observed
478 deviations of locus-wise clines from the genome-wide average would dictate the relative
importance of stochastic versus deterministic processes (Barton, 1983; Barton & Hewitt, 1985;

480 Slatkin, 1973; Vasemägi, 2006). We found eight transects that varied in either the width of locus-
wise transitions (β), or the direction of change in allele representation (α). Interestingly, ‘ α -
482 dominant’ transects were found within the Ozark region, previously hypothesized as being
naturally re-colonized from local refugia (i.e., $k2 \times k3E/S$, $k2 \times k6$, and $k4 \times k7$; Figs. 4, S2). This
484 hypothesis is also supported by state-wide surveys (1940’s) that found occupied WTD habitat
roughly corresponding with each Ozark sub-population (Figs. 7, S8).

486 All transects displayed near-zero β values across loci as well, suggesting either stochastic
processes (genetic drift, bottlenecks) or sampling artefacts as drivers of ancestry transitions,
488 given our expectation that a ‘true’ hard barrier between discrete populations would yield an
under-representation of inter-population heterozygotes (as described by β).

490 One interpretation of this result is that genetic drift at the edge of an expanding refugium
creates a ‘rolling’ founder effect, with alleles being over-represented ($\alpha > 0$) or under-represented
492 ($\alpha < 0$) across the re-colonized territory (Excoffier & Ray, 2008; Hallatschek & Nelson, 2008).
This phenomenon—termed “gene surfing”—can generate wholly neutral patterns that appear to
494 be adaptive (Peischl, Dupanloup, Bosshard, & Excoffier, 2016; Travis et al., 2007), and may
explain the presence of numerous α -outlier loci in those transects (Fig. 4).

496 Interestingly, all of our β -dominant transects crossed major rivers: Transect $k3 \times k6$
spanned the Arkansas River; $k3 \times k5$ the White River; and $k1 \times k8$ the Ouachita River. Transect
498 $k3 \times k4$ crosses the smaller Buffalo River, which may explain the depressed variability in cline
steepness (Fig. 4). Non-zero β values implicate variations on a sigmoidal cline shape, with values
500 describing rates of change in allele frequencies that are either steep ($\beta > 0$) or wide ($\beta < 0$).

Classically, clinal patterns are established by selection, or the existence of hard
502 boundaries to gene flow (Endler, 1973; Slatkin, 1973). However, spatially variable gene flow

coupled with drift can generate clinal patterns without necessitating selection across a
504 considerable proportion of the genome (Vasemägi, 2006). Selection could feasibly be involved,
at least for regions involving translocation of WTD subspecies, in that crosses between
506 subspecies have elicited fitness impacts such as dystocia (abnormal maternal labor due to shape,
size, or position of the fetus; Galindo-Leal and Weber 1994). Previous studies have also
508 underscored the genetic cost of inter-subspecific stocking (Hopken, Lum, Meyers, & Piaggio,
2015), such as anomalous variability in breeding time among other southern-recovered WTD
510 populations (Sumners et al., 2015). Some limited evidence also exists for a pheromonal basis for
reproductive isolation among mule deer subspecies [*Odocoileus hemionus*; (Müller-Schwarze &
512 Müller-Schwarze, 1975)].

514 **4.3 | Hunter-harvest and its management implications**

Our results identify within AR WTD a diagnosable genetic signature of historic translocations
516 within the genomes of extant populations. This simultaneously underscores the success of early
restocking efforts, while also reiterating long-standing concerns about the genetic and/ or
518 phenotypic impacts of anthropogenic translocations (Meffe & Vrijenhoek, 1988). It also
reinforces the need to formalize as an explicit management consideration the intraspecific
520 taxonomy of WTD, both to better understand the (yet to be seen) evolutionary consequences of
past translocations, and to provide a more proactive baseline going forward (Cronin, 2003;
522 Gippoliti, Cotterill, Groves, & Zinner, 2018).

Resource agencies, in particular, should prioritize those populations that retain endemic
524 genetic diversity, and by so doing, tacitly acknowledge the importance of preserving this
evolutionary legacy. Such recognition would capitalize on the many years of natural selection

526 that have operated on those populations prior to anthropogenic interference. It would also open
the door for potential variation in hunter-harvest, such as by having a restricted season strictly for
528 ‘legacy’ AR deer.

Our patterns of age- and sex-biased dispersal distances (Fig. 5, 6) largely recapitulate
530 expectations based on WTD life-history: Male dispersal established by the yearling cohort (Long
et al., 2008; McCoy, Hewitt, & Bryant, 2005; Shaw, Lancia, Conner, & Rosenberry, 2006);
532 females lack age-dependent dispersal (Lutz et al., 2015). The potential utility of the approach lies
within the context of a multi-state genetic monitoring program for WTD. While this would
534 necessitate inter-state investment and coordination, potential benefits of a ‘next-generation’
approach would be in preserving the evolutionary heritage of WTD, supporting the adaptive
536 management of a biodiversity resource of national importance, as well as promoting the strong
tradition of hunting in North America (Geist, Mahoney, & Organ, 2000).

538

4.4 | CWD expansion and its management implications

540 Our results also suggest the existence of several discontinuities in gene flow across the state.
Given that CWD is a paramount issue in the global management of WTD (Rivera, Brandt,
542 Novakofski, & Mateus-Pinilla, 2019; Uehlinger, Johnston, Bollinger, & Waldner, 2016), a
valuable application of our results would be towards disease containment. Given that the spread
544 of CWD will be more rapid within rather than among populations, monitoring efforts should
focus on detecting ‘breaches’ between genetically distinct regions (which are most often divided
546 by major rivers and urban centers, as herein; Fig. 3). Interestingly, the current boundaries for the
AGFC ‘Deer Management Units’ (DMUs) (Meeker et al., 2019), are remarkably consistent with
548 many of the intraspecific suture zones identified in our study. Thus, potential mitigation efforts

should work to constrain the transportation of potentially infectious material (such as carcasses)
550 from CWD-detected DMUs. Management actions should reduce the outward dispersal of
individuals from DMUs, and one approach is to reduce the density of yearling males, which
552 often comprise >50% of emigrating individuals (McCoy et al., 2005; Nelson, 1993; Nixon,
Hansen, Brewer, & Chelsvig, 1991). A similar action could be management to reduce local
554 population densities. The latter, in turn, acts to drive dispersal in that robust population numbers
are a catalyst for increasing social pressure as well as resource competition (Long et al., 2008;
556 Lutz et al., 2015; Shaw et al., 2006).

One harvest strategy ['Quality Deer Management,' QDM; (Brothers and Ray, 1975;
558 Hamilton et al., 1995)] has several management goals operating in parallel to improve WTD
demography. These are: Actively decreasing overall population density; elevating the proportion
560 of mature males in the population; and increasing the female component of the sex ratio. The
success of this approach was assayed by evaluating WTD emigration rates pre- and post-
562 application (Shaw et al., 2006). Two important aspects were noted: Emigration probabilities
decreased, as did mating behavior of yearling males. The implications of a management strategy
564 focusing on these explicit goals would be a serious reduction in CWD dissemination. It is unclear
how this paradigm could impact long-term disease trajectories within CWD-prevalent DMUs,
566 although lower emigration probabilities and decreased densities would concomitantly depress the
probability of disease contraction for a given individual.

568

4.5 | Selection for CWD genetic variants and its management implications

570 Previous CWD research in WTD populations has focused on the prevalence of a polymorphism
in the *PRNP* gene [responsible for the malformed protein product that constitutes the prion agent

572 of CWD (Johnson et al., 2011; Race, Meade-White, Miller, Fox, & Chesebro, 2011; Rivera et al.,
2019)]. Those WTD exhibiting a non-synonymous transition at amino acid residue 96 (from G to
574 S) had decreased susceptibility to CWD. This variant had a significantly greater presence among
older individuals in CWD-detected areas, suggesting increased survivability for those individuals
576 manifesting that variant (Chafin et al., 2020; Douglas et al., 2020). Results herein support this
result, in that older males (>4 years) are genetically more similar to neighboring individuals than
578 to younger males (Fig. S6). This in turn suggests a non-linear increase in reproductive success
with age [or perhaps with other collinear factors as well, such as body weight or antler size
580 (Newbolt et al., 2017)].

Directing management efforts towards an older age-structure could therefore have an
582 ancillary benefit in that it would promote the relative reproduction of individuals having the 96S
variant, given its presence at a significantly higher probability among more mature individuals
584 (Douglas et al. 2020b). Our results could also be used to explore those environmental variables
potentially responsible for resistance to movement at the landscape-level. This aspect, in
586 conjunction with ongoing work on spatially variable genetic susceptibility, could promote the
development of risk assessment models that assay disease spread.

588

DATA AVAILABILITY STATEMENT

590 All raw sequence files will be accessioned in the NCBI Sequence Read Archive (SRA) under
BioProject XXXXXX following acceptance; relevant curated (i.e. assembled and filtered) data
592 will be archived on Dryad (doi: XXXXXX); codes and custom scripts developed in support of
this work are also available as open-source via GitHub under the GNU Public License:
594 github.com/tkchafin (and as cited in-text).

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926 **Figures and Tables**

928 **Figure 1: Ancestry proportions for 1,143 Arkansas white-tailed deer**, as inferred using the
program ADMIXTURE. Samples are represented as pie charts plotted at absolute collection
930 coordinates, with colors of assignment probabilities proportional to a particular subpopulation.

932 **Figure 2: Assignment probabilities for eight populations ($k=1$ through $k=8$)**, interpolated
using Empirical Bayesian Kriging. $P(k)=1.0$ corresponds to 100% probability of ancestry per
934 raster cell, and $P(k)=0.0$ corresponds to 0%. Individual samples are represented as black dots.

936 **Figure 3: Simpson's diversity of interpolated ancestry proportions.** Each raster cell was
assigned 8 values equal to the expected proportion of ancestry corresponding to the 8 genetic
938 clusters (Fig. 1), then summarized by calculating Simpson's diversity index.

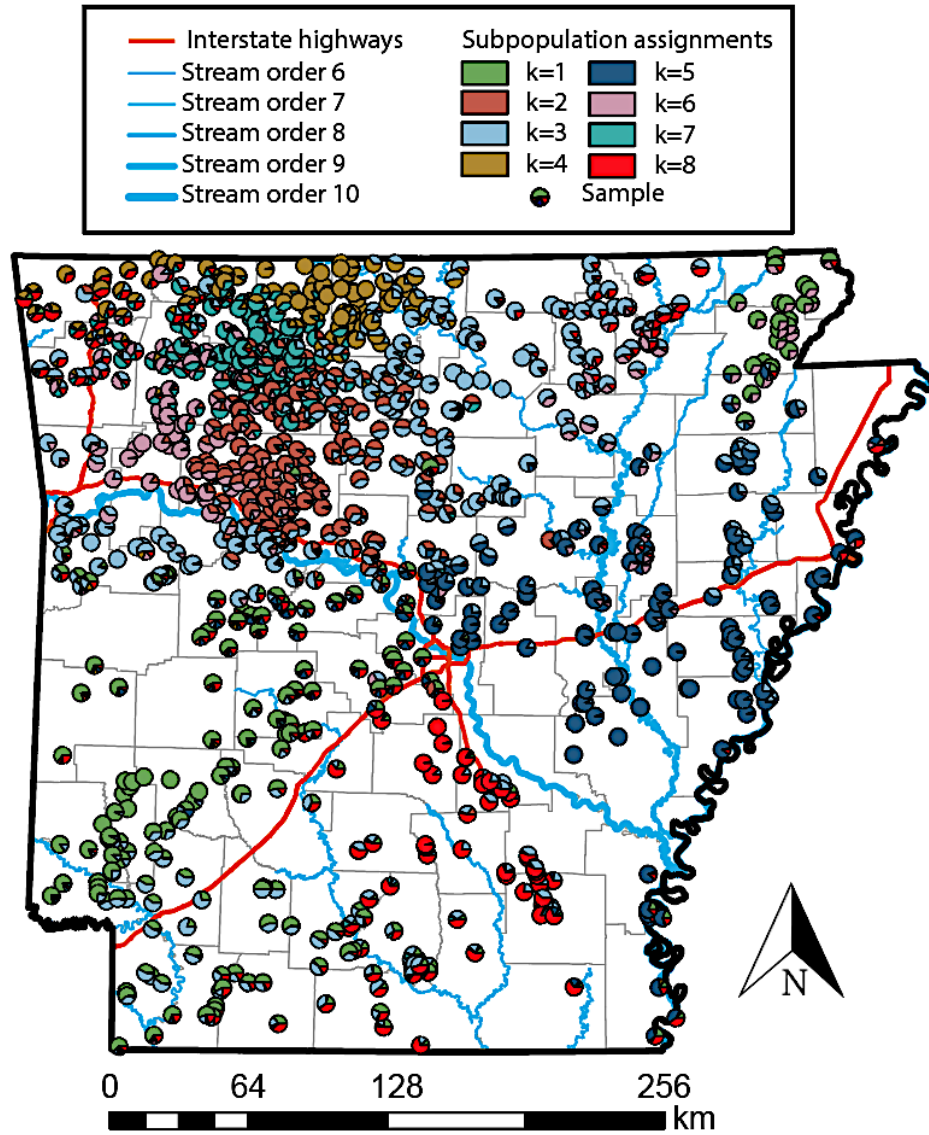
940 **Figure 4: Relationships between genomic cline parameters** contrasted among eight sub-
sampled transects of intraspecific suture zones in white-tailed deer (Fig. 3). Contour plots show
942 relative densities of SNPs varying in cline rate (β), representing the steepness of clines, and cline
center (α), representing bias in SNP ancestry. Outlier loci are highlighted in blue.

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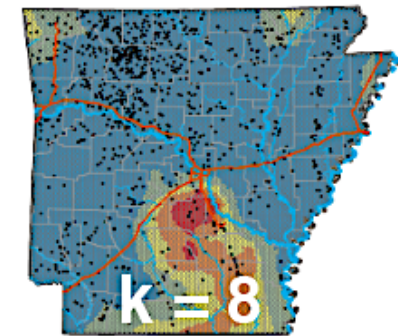
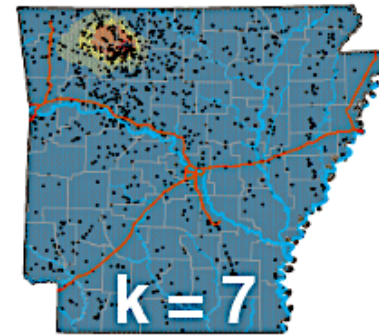
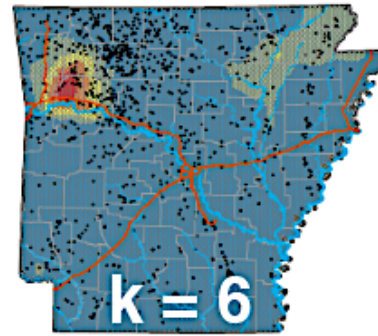
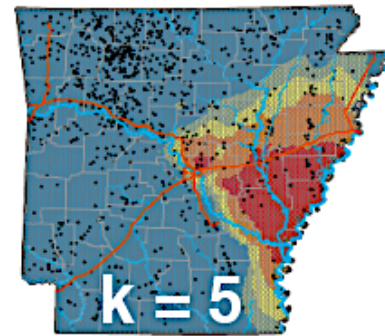
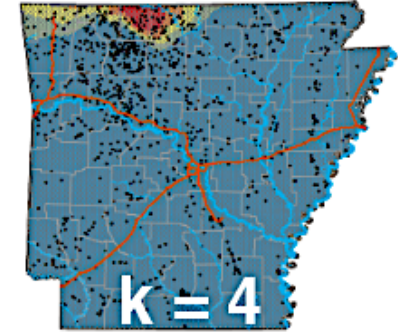
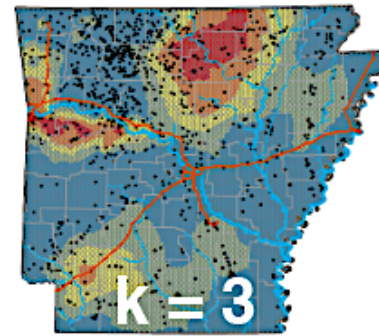
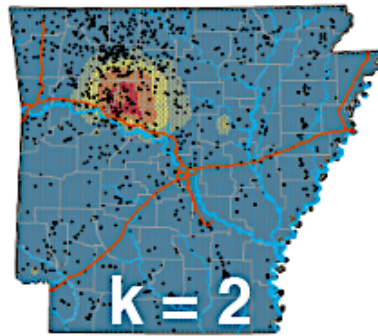
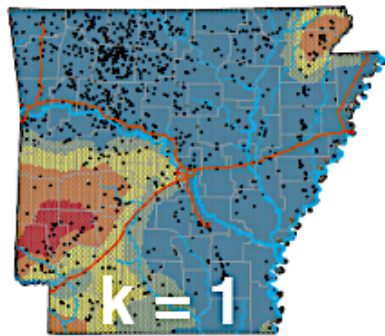
Figure 5: Summary of geo-location predictions in LOCATOR as a random subset of N=490
946 individuals, at two error thresholds: 10km (=A) and 20km (=B), thus constraining results to
N=110 (=A) and N=264 (=B). Error calculated as mean distance of bootstrap predictions from
948 the centroid predicted for each individual (see Fig. S4). A black dot denotes the predicted
location of an individual and a colored dot indicates the 'true' location (colors proportional to
950 measurement error in km).

952 **Figure 6: Inferred dispersal distances, partitioned by sex and age class.** Dispersal distances
were calculated as the difference (in km) between the predicted and true locations, excluding all
954 individuals with a mean prediction error of 10km (see Figs. 14-15). Sample sizes for each group
are given in black, with the mean in red below each box plot. P-values are reported for within-
956 age two-sample t-tests comparing means from males and females.

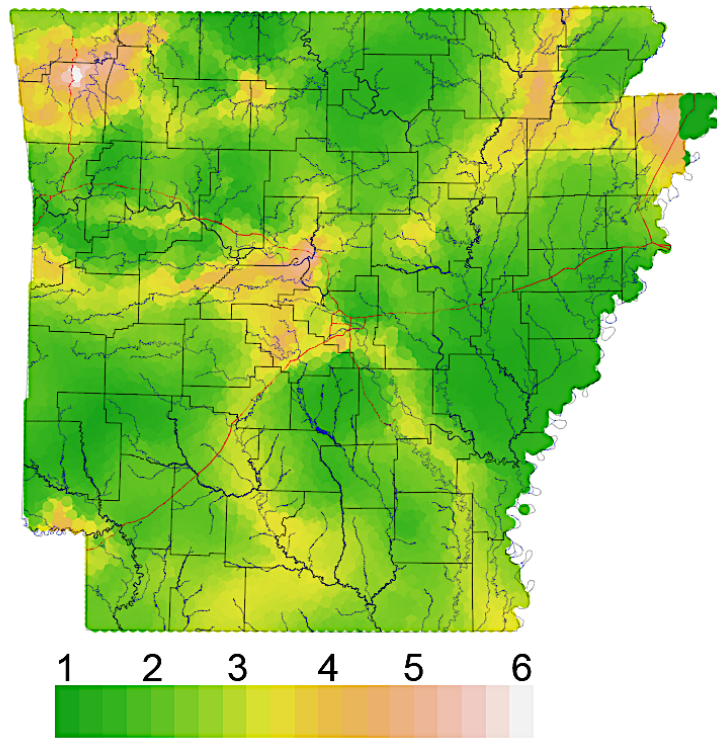
958 **Figure 7: Proposed translocation pathways and refugial populations in Arkansas**, showing
(left) translocation events supported by genetics along (dashed line), as well as those with
960 anecdotal support given limited historical records (solid), from three primary stocking sources:
Sandhill Game Farm in Wisconsin (W); ‘Sylamore District’ state refuge sites (S); and the
962 Howard County Game Farm (H). Also shown are major inhabited regions of white-tailed deer
(right) estimated from 1942-47 game surveys, excluding small regions (see full version in Online
964 Supplementary Material). Putative inhabited regions are also annotated according to their
hypothesized associations with contemporary genetic clusters (Fig. 1-2).

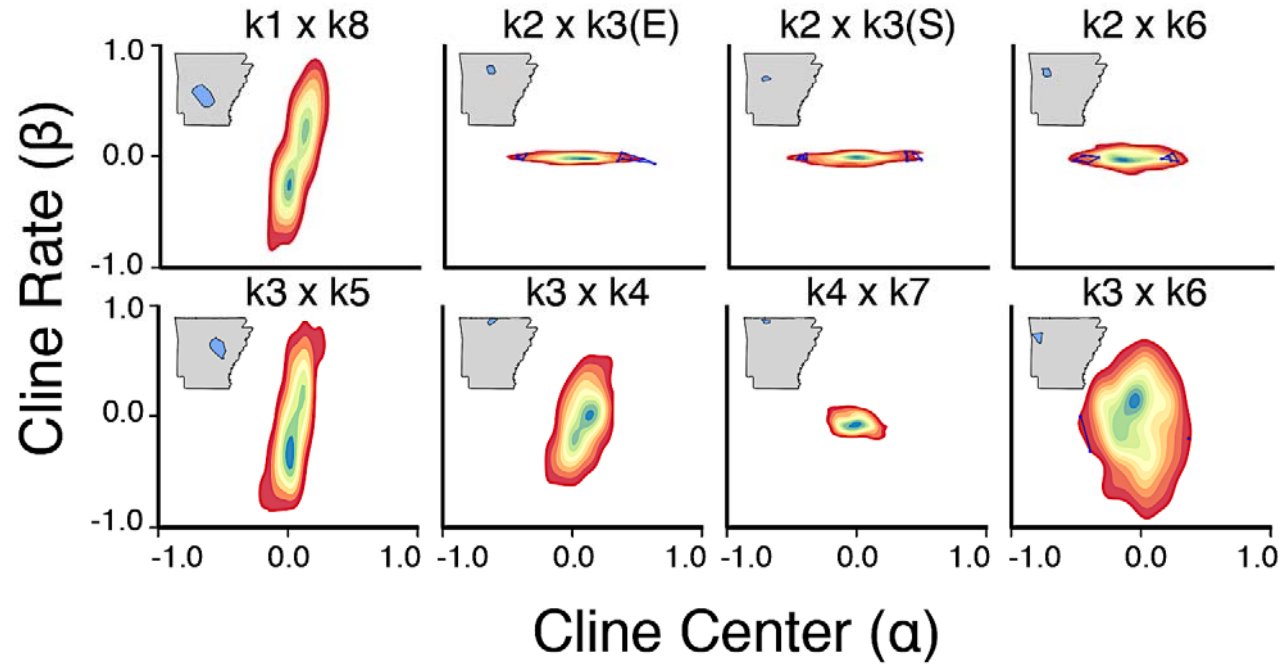


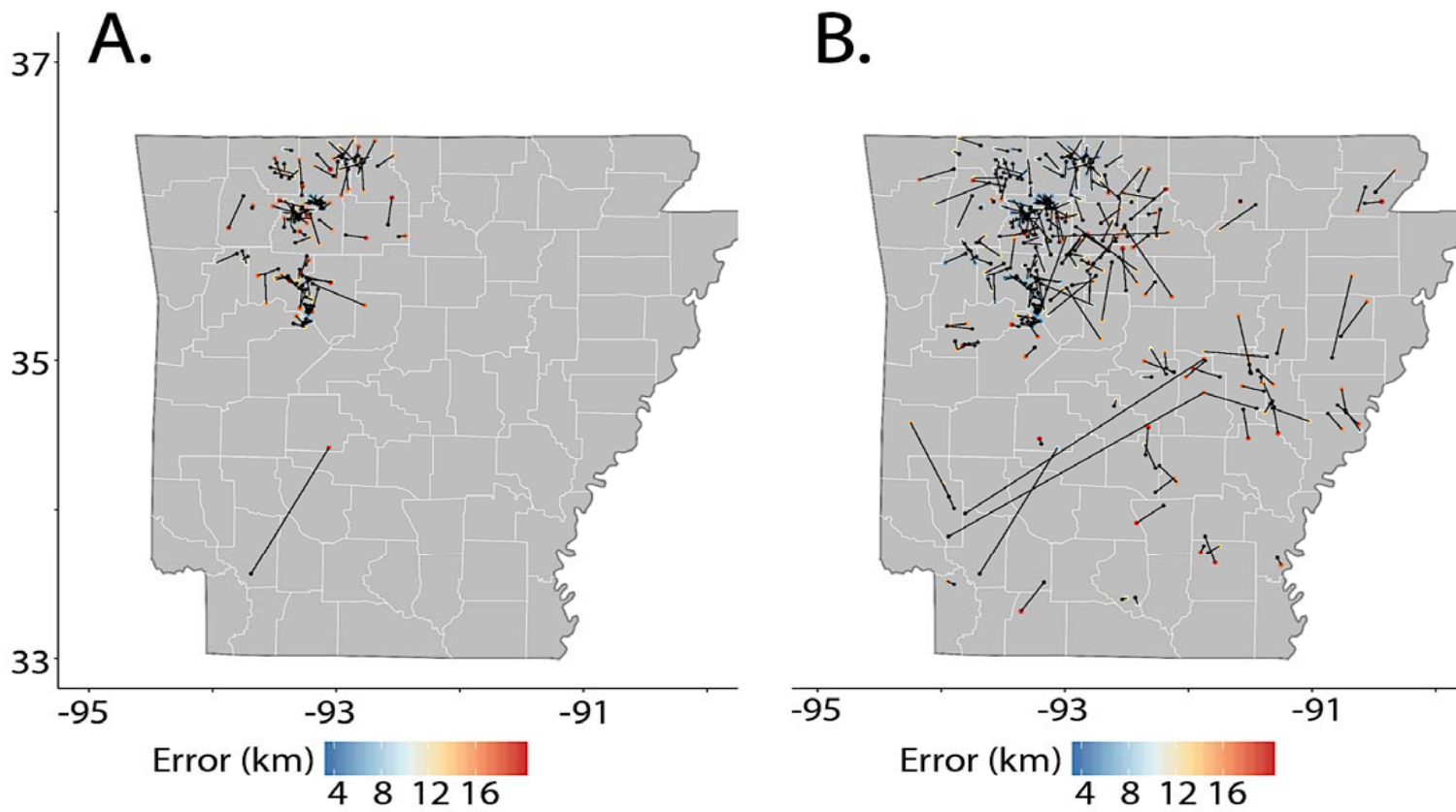
Assignment probability

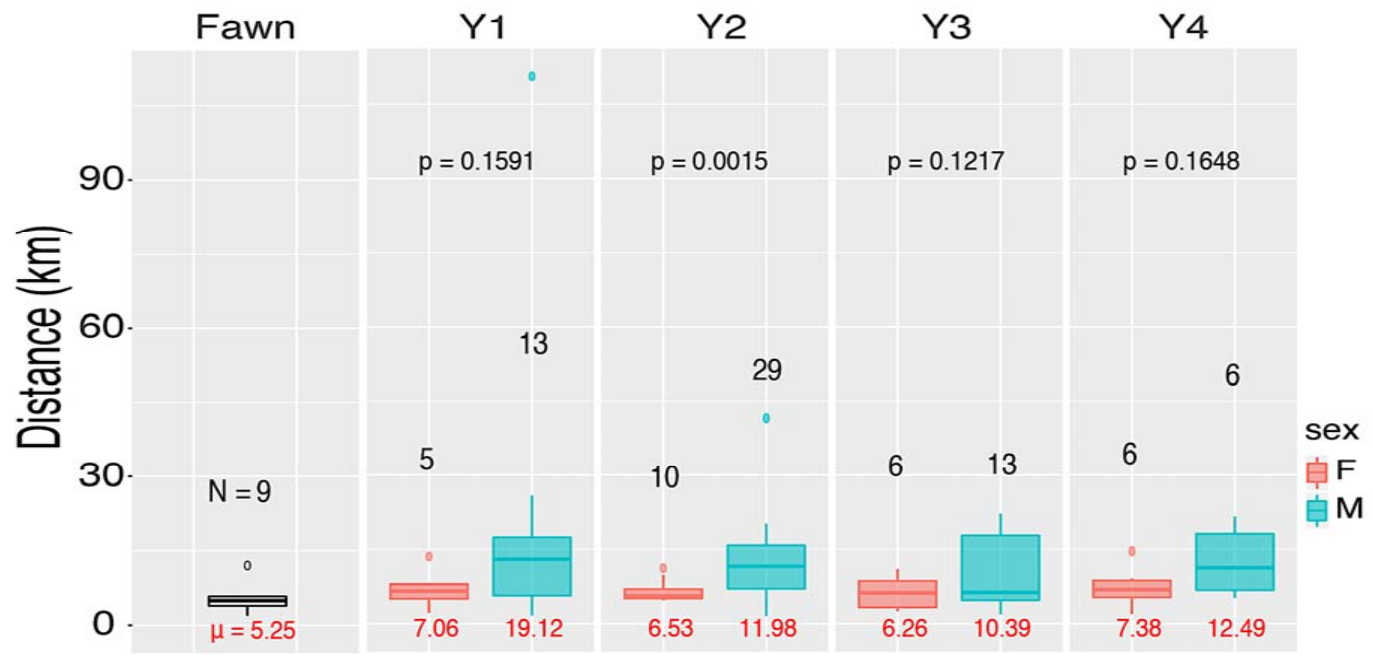


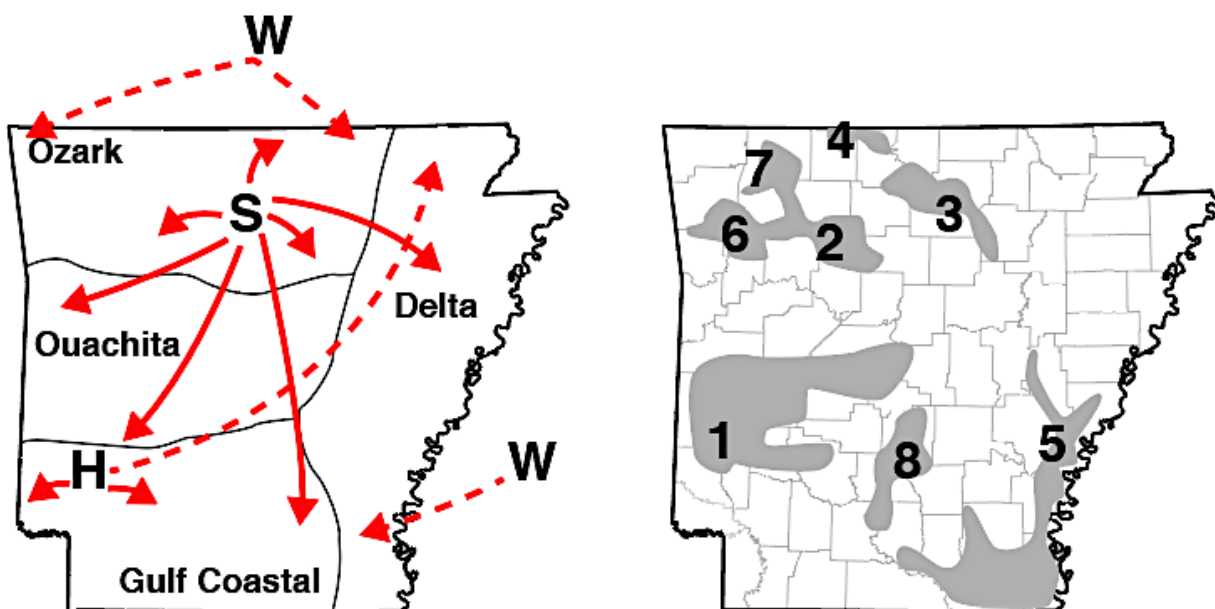
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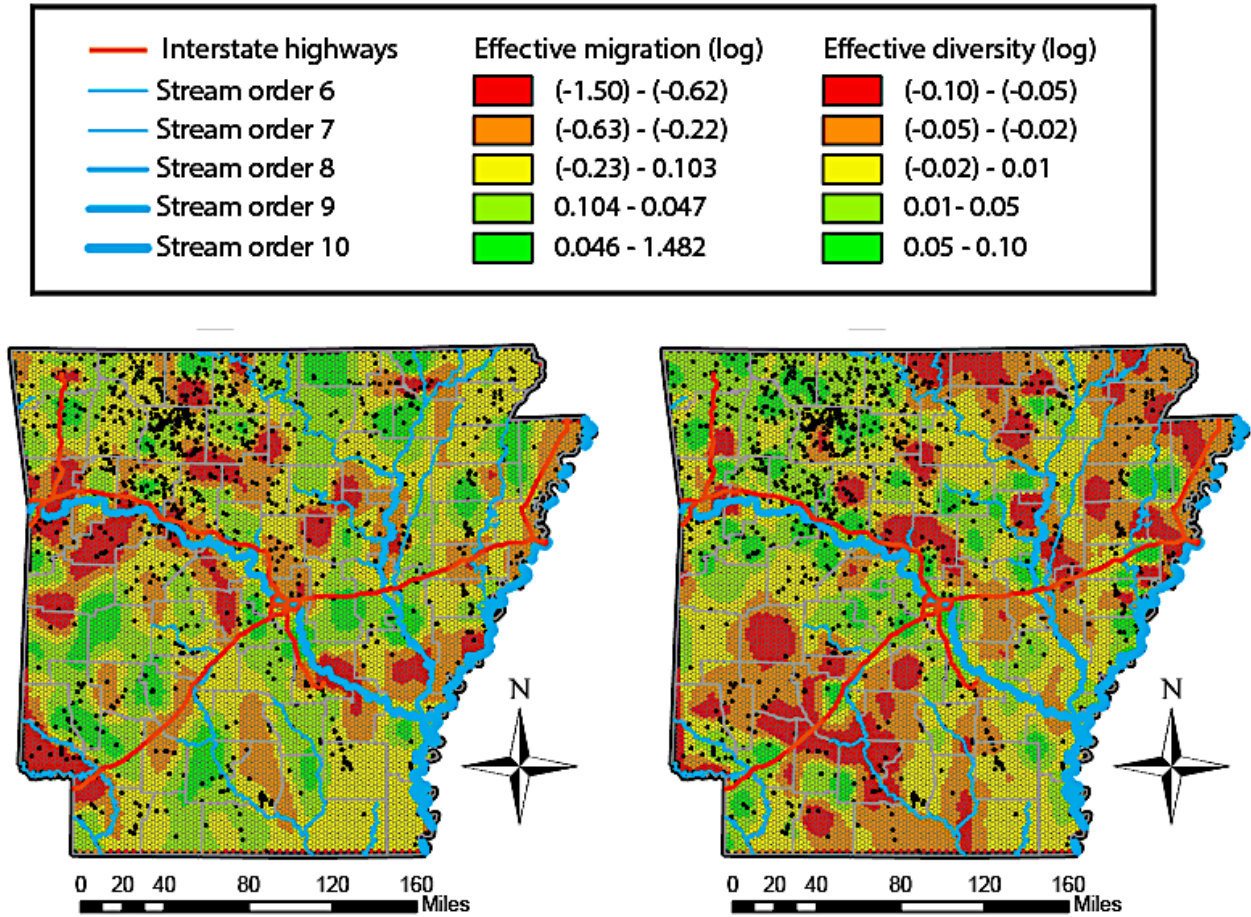
979 **Supplementary Figures and Tables**

980 **Table S1:** Numbers (=N) of white-tailed deer genotyped across ~35,000 SNP loci. Samples were
 981 collected from 75 counties (=County) in Arkansas (2016-2019). Code indicates standard 2-letter
 982 county abbreviation. Samples removed due to missing data are not included.
 983

County	Code	N	County	Code	N
Arkansas	AR	11	Lee	LE	9
Ashley	AS	1	Lincoln	LI	8
Baxter	BA	19	Little River	LR	10
Benton	BE	19	Logan	LO	32
Boone	BO	34	Lonoke	LN	11
Bradley	BR	2	Madison	MA	39
Calhoun	CA	14	Marion	MR	39
Carroll	CR	50	Miller	MI	8
Chicot	CH	3	Mississippi	MS	2
Clark	CL	7	Monroe	MO	10
Clay	CY	15	Montgomery	MN	2
Cleburne	CE	8	Nevada	NE	13
Cleveland	CV	5	Newton	NW	140
Columbia	CO	4	Ouachita	OU	12
Conway	CN	11	Perry	PE	8
Craighead	CG	7	Phillips	PH	9
Crawford	CW	6	Pike	PI	8
Crittenden	CT	8	Poinsett	PO	10
Cross	CS	10	Polk	PL	3
Dallas	DA	7	Pope	PP	62
Desha	DE	11	Prairie	PR	10
Drew	DR	14	Pulaski	PU	11
Faulkner	FA	14	Randolph	RA	8
Franklin	FR	20	Saline	SA	11
Fulton	FU	9	Scott	SC	2
Garland	GA	14	Searcy	SE	32
Grant	GR	5	Sebastian	SB	17
Greene	GE	16	Sevier	SV	12
Hempstead	HE	9	Sharp	SH	16
Hot Spring	HS	3	St. Francis	SF	7
Howard	HO	11	Stone	ST	15
Independence	IN	7	Union	UN	6
Izard	IZ	6	Van Buren	VB	23
Jackson	JA	2	Washington	WA	17
Jefferson	JE	13	White	WH	10
Johnson	JO	45	Woodruff	WO	9
Lafayette	LA	14	Yell	YE	31
Lawrence	LW	17	Total		1,143

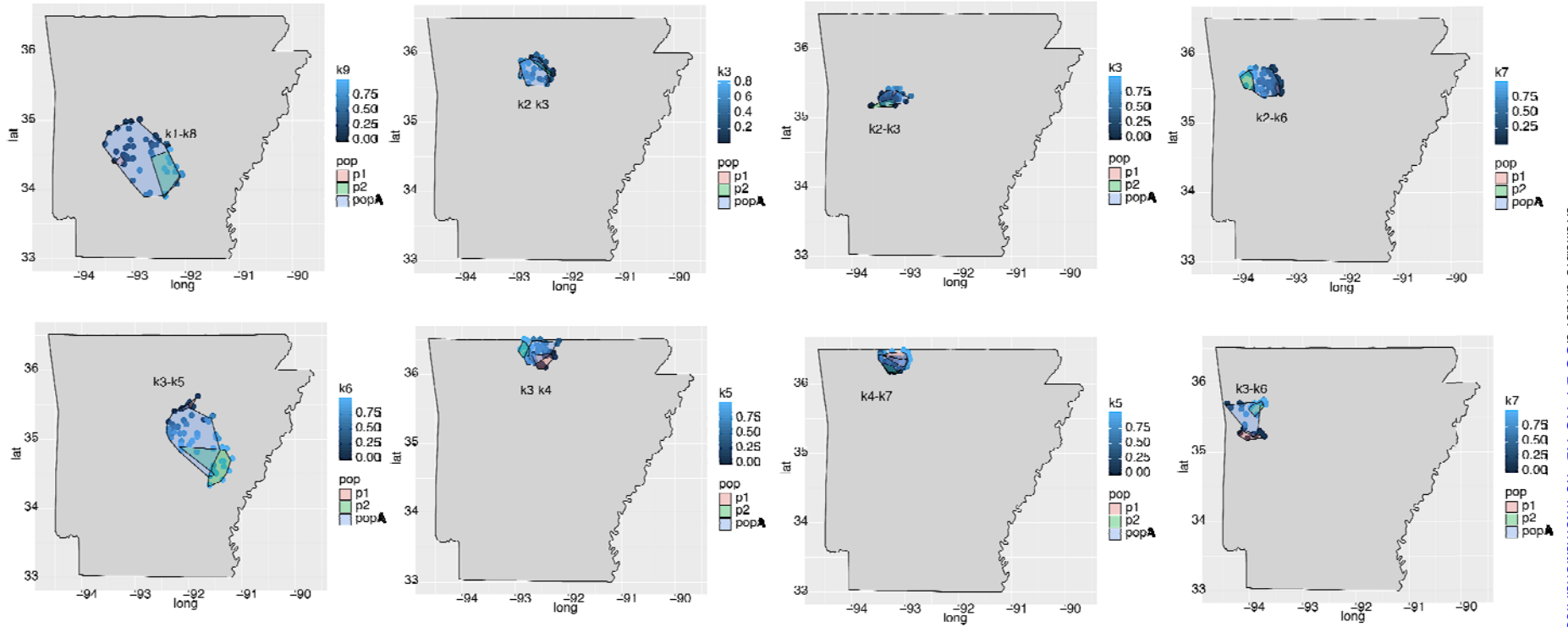
986 **Figure S1: Effective migration rates and intra-population diversity** (\log_{10} scale), calculated
from effective migration surfaces (EEMS). Rates are plotted according to colored bin, with
divisions calculated as natural breaks using the Jenks algorithm in ArcMAP.

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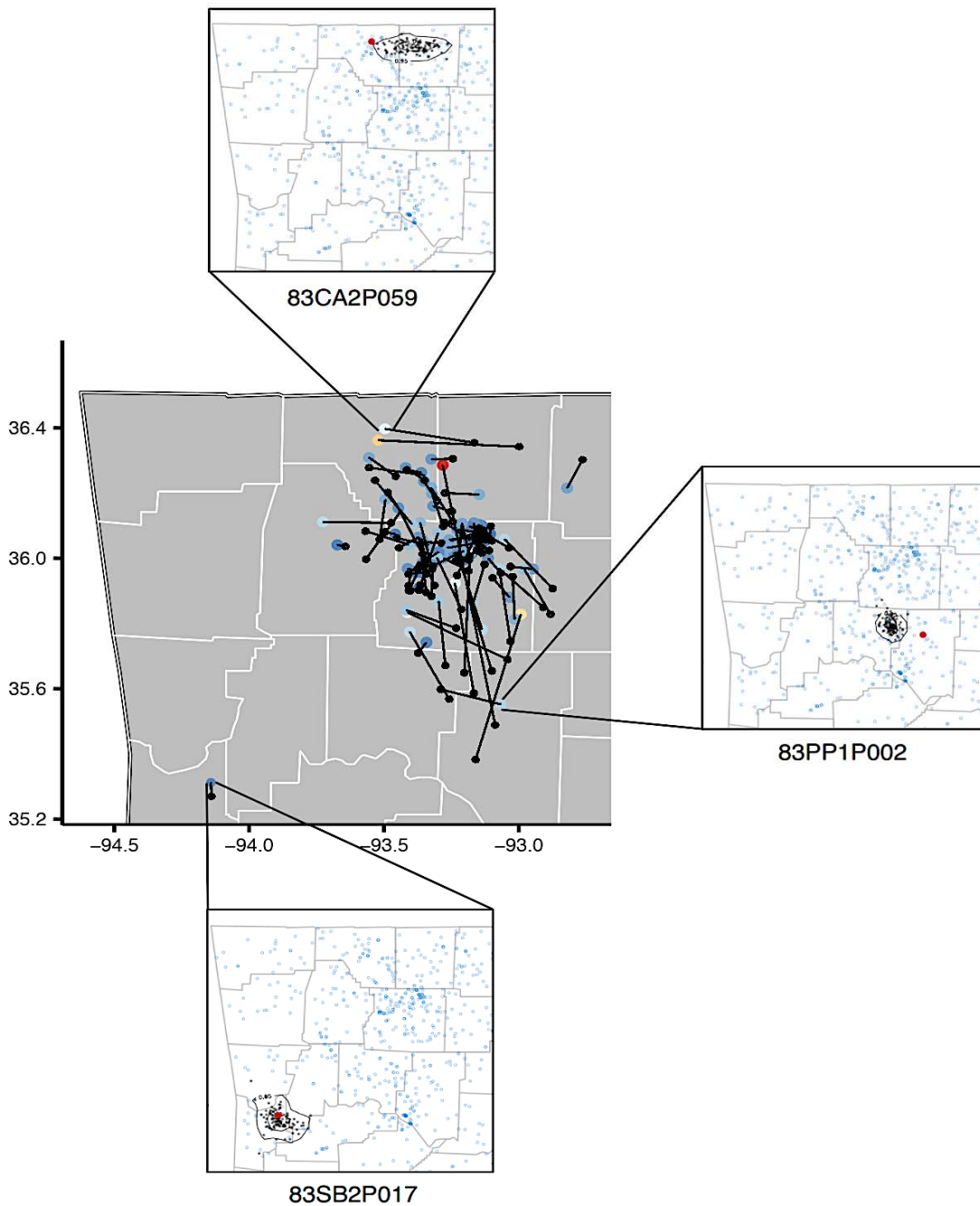
990

992 **Figure S2: Sampled transects employed for genomic cline analysis with selected groups within each coalesced within colored**
994 hulls: Reference population 1 (p1; red); Reference population 2 (p2; green); and putative admixed individuals (popA; blue).

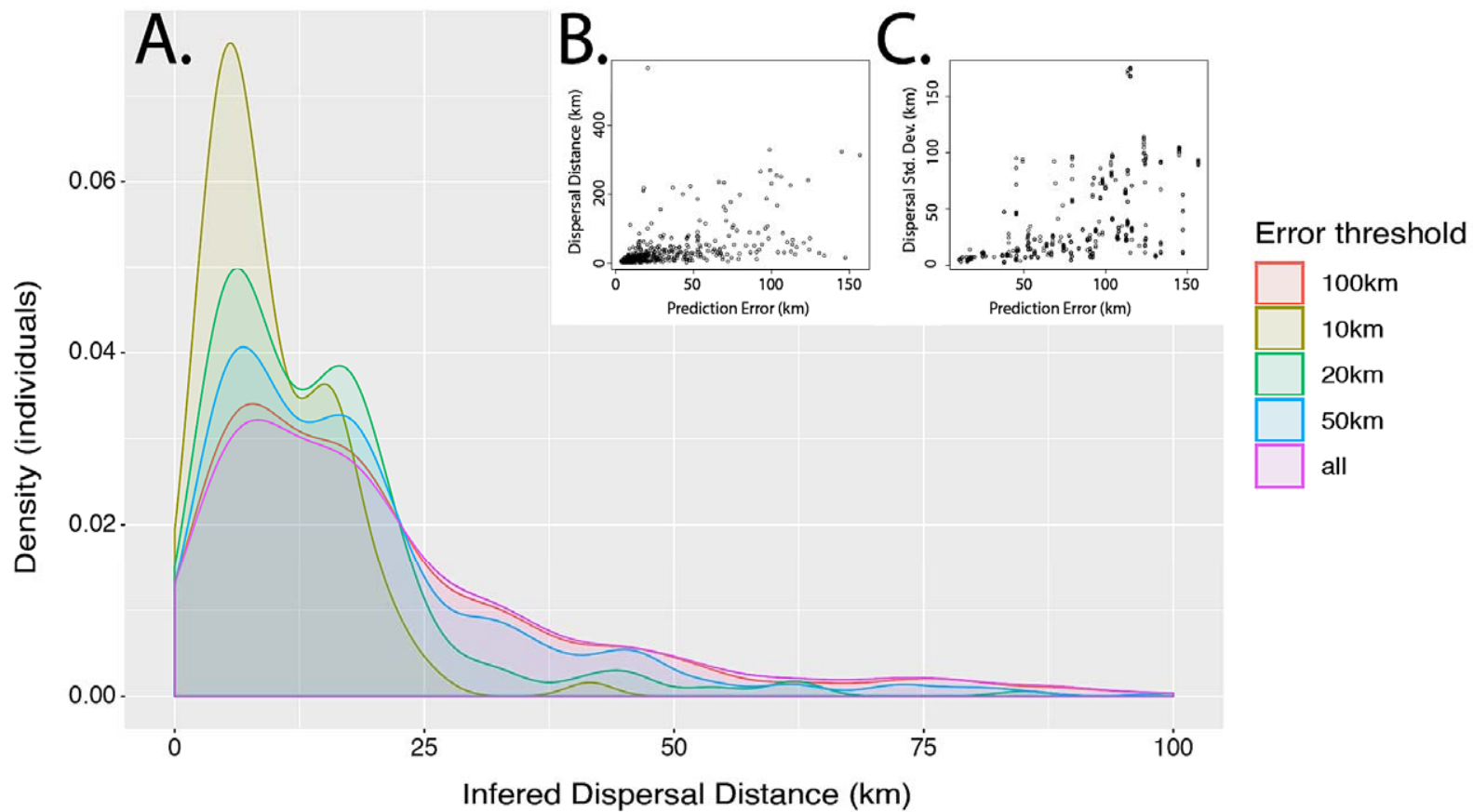


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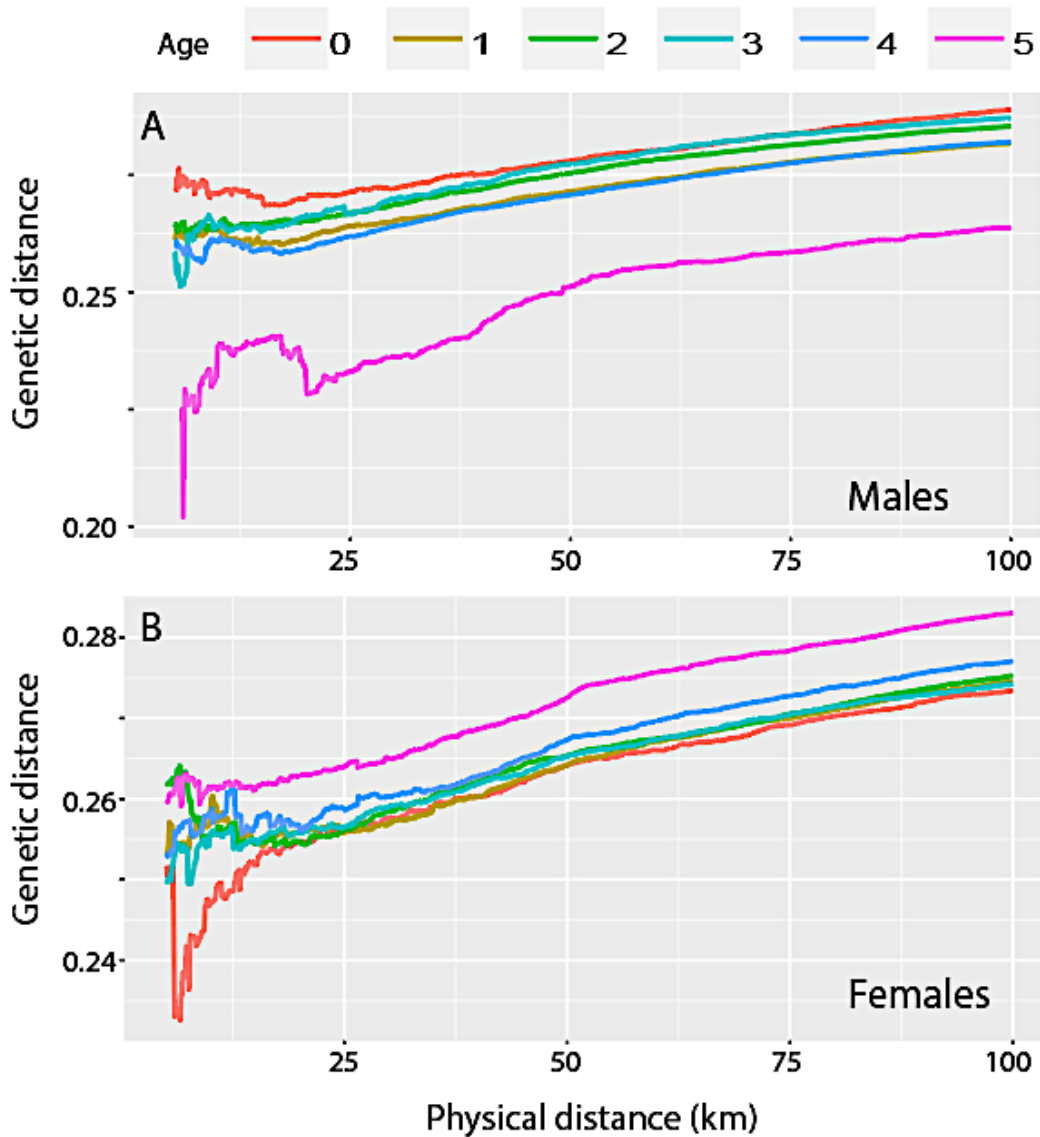
996 **Figure S3: LOCATOR Geo-located results for CWD-positive individuals derived via**
997 **LOCATOR.** Individuals are represented by dots, pairs of which are connected by a single line.
998 A black dot denotes predicted location, while a colored dot indicates ‘true’ (observed = sampled)
1000 location (color proportional to distances separating each). Inserted figures offer full prediction
results for three selected samples, with bootstrap estimates demarked by a 95% contour.



1002 **Figure S4: Effects of error thresholds on inferred dispersal distances as predicted by LOCATOR analysis.** Inferred dispersal
1004 kernels were computed at several error thresholds: (A) Error computed as mean distance of predicted coordinates for each individual
at 100 bootstrap estimates from predicted centroid (=interpretation of localized vs. dispersed predictions). Dispersal distances
1006 calculated as difference (in km) between predicted centroid versus ‘true’ (observed) location. Inferred dispersal distances generally
increase for individuals with larger prediction error; (B) Larger stochastic variation in centroid location for individuals with lower
1008 predicted precision among bootstraps; (C) Standard deviation of dispersal distances for the latter computed in a sliding window of
10km along the x-axis (prediction error).



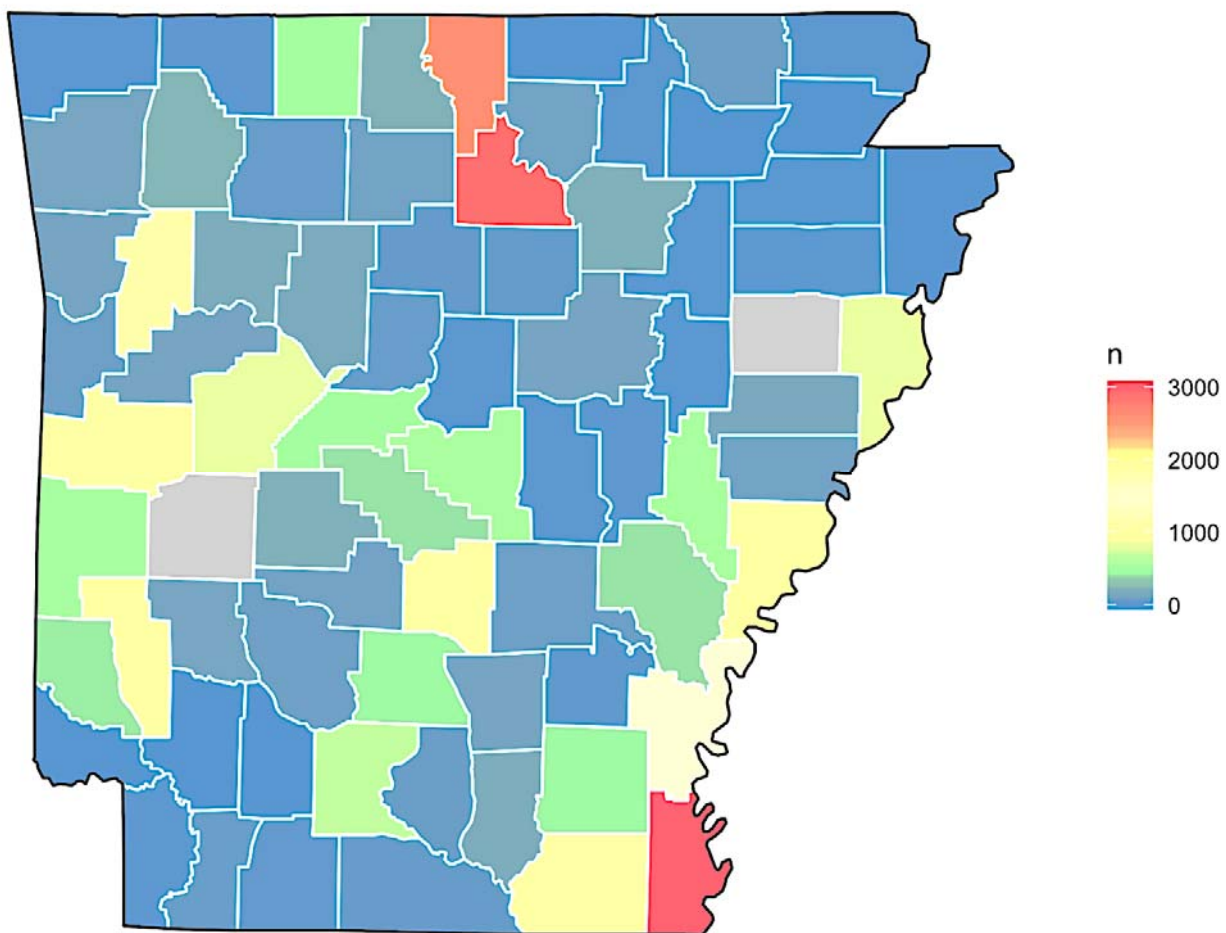
1010 **Figure S5: Spatial patterns of genetic dissimilarity among white-tailed deer partitioned by**
1012 **age and sex.** Genetic distances between individuals and neighbors derived from 5,000 randomly
1014 sampled SNPs depicted across physical distance (x-axis). Results depict different cohorts of
males (A) and females (B) by age.



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Figure S6: Census estimates for white-tailed deer from surveys in 1942-1946

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1034 **Figure S7: Subpopulation probabilities overlain with ‘deer occupied territories’ circa 1942-**
1035 **1947 (in green).** Polygons representing deer occupation were manually compiled from the
1036 Wildlife and Cover Map of Arkansas (1942-47), prepared by Arkansas Game and Fish
1037 Commission in cooperation with U. S. Fish and Wildlife Service as one aspect of a Federal Aid
1038 Project (drawn by Flaun M. Tolar). Map accessed from the University of Arkansas Library
1039 Arkansas Collection (Special Collections). A higher resolution geo-referenced version available
1040 at a later date (reproduction/ copy permissions granted by University of Arkansas Libraries).

