Supplementary Information

Proximity among protected area networks promotes functional connectivity for wintering waterfowl

Nicholas M. Masto[1,*†], Allison C. Keever[1,†], Cory J. Highway[1], Abigail G. Blake-Bradshaw[1], Jamie C. Feddersen[2], Heath M. Hagy[3], Bradley S. Cohen[1]

[1]Tennessee Technological University, College of Arts and Sciences, Cookeville, TN, USA

[2]Tennessee Wildlife Resources Agency, Migratory Gamebird Program, Nashville, TN, USA

[3]United States Fish and Wildlife Service, Refuge System, Southeast Region, Stanton, TN, USA

[*]Corresponding author: nmasto1214@gmail.com | Current Affiliation: Cornell Lab of Ornithology, Center for Avian Population Studies, Ithaca, NY, USA

[†]Shared first authorship

1. Supplementary Context, Methods, Results

Appendix 1 – Aerial surveys to index hunting: empirical evidence of a hostile landscape matrix surrounding sanctuary nodes

Context

Island biogeography theory is contingent upon the assumption that the landscape matrix between suitable patches is inhospitable[1,2]. However, most studies evaluating insular predictions within non-island environments lack empirical evidence that the matrix surrounding protected areas is truly "non-usable" to focal animal(s). We assumed waterfowl sanctuaries were the only suitable patches of habitat for mallards and other waterfowl diurnally within our protected sanctuary network which was a reasonable assumption based on contemporary data[3,4]. Nevertheless,

waterfowl and other wetland-dependent gamebirds can theoretically use private or publicly-owned wetlands that are hunted periodically (i.e., temporal sanctuary)[5,6]. We implemented aerial surveys across the Tennessee portion of our study region from 2019–2022 and modeled the spatial and temporal frequency of hunting to ensure the landscape matrix surrounding protected sanctuary nodes met assumptions of reasonable unsuitable habitat patches diurnally. Specifically, we recorded the presence of spinning-wing decoys to index active hunting parties, given their ubiquitous use by waterfowl hunters across North America and elsewhere[7].

Briefly, these data and supplemental modeling of hunting provided empirical evidence to justify our assumption that sanctuary nodes were "islands" of suitable habitat diurnally within an otherwise unusable landscape matrix. Secondarily, predicted hunting intensities provide additional support for limited and proximity-biased sanctuary transitions (Fig. S1).

Methods

We implemented aerial transect surveys across the Tennessee study region and its sanctuary network from 2019–2022 to inform hunting frequency and distribution. We conducted aerial surveys at ~weekly-biweekly time intervals. We initially created a sample frame of 495 (18,257 km) transects and sampled transects systematically and proportional to their length within each river drainage strata (Obion, Mississippi, North, and South Forked Deer) at ~6% based on available funds[8]. We quickly realized wasted survey effort due to channelized riverine systems[9] and adapted transects by deleting those that could never be inundated and systematically sampled new transects within river tributaries. Last, we optimized transportation to and from transects by selectively adding transects along river tributaries that transitioned aerial observers to the next transect or deleting portions of transects based on preliminary surveys and experience[9].

During the first survey of each year (mid-November to early December), we censused all waterfowl hunting blinds along aerial transects. In subsequent surveys, the observer enumerated and recorded GPS locations of waterfowl hunting blinds and presence/absence of spinning wing decoys. The presence of spinning-wing decoys indexed active hunting risk given their ubiquitous use by waterfowl hunters in west Tennessee and elsewhere[7]. For example, 88% of hunters in Arkansas used spinning-wing decoys in 2001–2002[7]. Our surveys suggested similar or greater use of spinning wing decoys by the waterfowl hunting community in Tennessee. We alternated each survey initiation time by geographic strata (i.e., Obion River, North Forked Deer, South Forked Deer, and Mississippi River floodplains) to obtain a representative and unbiased sample of hunting across the entire landscape by controlling for the effect of greater hunting risk in the morning compared to later in the surveys.

Testing for temporal effects of hunting

We assessed the effects of time on hunting risk by summing the number of spinning decoys observed for every hour across all surveys and modeled counts against time variables. We used the *fitdistplus* package in R version 4.2.2 to compare log-normal, Poisson, and negative binomial error distributions against the empirical distribution across 100,000 bootstrap replicates [10,11]. We selected the error distribution that minimized Akaike's Information Criterion (AIC) which was the log-normal distribution (AIC = 845)[12]. We fitted log-linear ordinary least squared regression models of spinning wing decoys against survey year (2019–2020, 2020–2021, 2021–2022), week of the year (1–9), day of the week (weekend or weekday), and hour of the day (1–16). We tested for an interaction between hour × week because we predicted hunters may stay afield longer later in the season. All other variables were additive. Briefly, there was no difference among survey

years, which justified pooling spinning-wing decoy observations across years for spatial predictions.

Spatial predictions of hunting risk – the "inhospitable" landscape matrix

We generated 1 km^2 grids along every aerial transect surveyed from 2019–2022. Within each grid cell, we summarized the number of observations (0…*n* spinning-wing decoys) and the sum of recorded spinning wing decoys within each cell (0…*n*). The sum of spinning wing decoys represented the intensity of active hunting per 1 km^2. We supplemented recorded zeros with pseudo-absences where each 1 km^2 grid cell that never had a spinning-wing decoy observation across the three years of the survey was populated with a zero[8,13]. Next, we retrieved or generated raster images to predict counts and variation in spinning wing decoys. Predictive raster images included (1) a digital elevation model; (2) estimated slope; (3) parcel sizes; (4) human access index; (5) distance to rivers; (6) distance to developed areas; (7) distance to waterfowl sanctuary; (8) eight landcover categories; (9) inundation frequency; and (10) estimated kernel density of hunting blinds:

1. We retrieved the DEM from USGS's online repository through GEE.
2. We used the DEM to estimate slope using the *ee.Terrain.slope* function in GEE[14].
3. We retrieved parcel sizes for Tennessee and Arkansas which were freely available on their GIS clearing houses, respectively. Parcel sizes for Kentucky and Missouri were unavailable and were assigned null values.
4. We generated a categorical raster of human disturbance with four designated categories including waterfowl sanctuary (i.e., no hunting), public-hunted areas with weekly designated 3-day hunting and 4 days of no hunting (i.e., regulated hunting and human disturbance), public-hunted areas that regulated through a draw system or were open to

the public but could be hunted daily (i.e., intense hunting), and private lands which had unregulated human disturbance and hunting (i.e., unknown–intense hunting)[4].

5. We used the *distance accumulation* tool in ArcGIS Pro to generate distance-based rasters which calculated distance (km) from a specified geographic feature to each 30 × 30 m pixel across the study region. The first distance raster was distance from rivers.
6. The second distance-based raster was distance from waterfowl sanctuary.
7. The third distance-raster was distance to developed land. We used all three intensities of "developed land" categories from the NLCD for the distance to developed raster[15].
8. We used U.S. Department of Agriculture's CDL and reclassified landcover into corn, rice, sorghum, soybeans, cotton and other agriculture, developed lands, emergent wetlands, and open water.
9. We used the SEIF data layer that indexed annual flood frequency[16].
10. Last, we combined recorded observations of waterfowl hunting blinds from aerial surveys which encompassed a significant proportion of private lands, combined observed hunting blinds with state-owned and georeferenced waterfowl hunting blinds, and used a kernel density estimator with a 2,500 m radius to illustrate "hunting hotspots" as our final covariate to predict hunting risk and variability[17].

We trained random forest regressions in ArcGIS Pro to predict hunting intensity across seasons[18]. We trained the forest with 1,000 trees, specified 5 observations as the minimum required for a terminal node (i.e., minimum leaf size) for each tree, and included $\sqrt{10\ predictors} = 3$ randomly sampled predictor variables to include in each decision tree[19]. Last, we used a data-driven approach allowing each tree to optimally select the maximum number of splits along a tree (i.e., maximum tree depth)[19,20]. We withheld 10% of the data and

iterated a single forest 50 times during training to subsequently estimate a distribution of variable importance (VI) scores and model performance (R^2). The VI metric is calculated using Gini coefficients (*G*), where the sum of error reduction resulting from tree splits for a specific variable is measured relative to the statistical significance of the split across all decision trees[21,22]. In other words, VI (summed *G*s) represents the overall effect of each variable in driving model predictions. In addition to (R^2), we calculated the out-of-bag root mean squared error [RMSE] to assess average prediction error[18,23]. We used the trained model iteration that minimized our loss function (RMSE) and maximized accuracy (R^2) for spatial predictions. Last, we reclassified relative hunting intensity to zero within waterfowl sanctuaries boundaries because of known true zeros associated with these areas (i.e., no hunting).

Results

Aerial surveys began at approximately 0700 and ended around 1600 on average. Active hunting did not differ temporally among years, week of the year, or weekends versus weekdays (Table S2). Hunting only varied daily, declining from 13.0 (95% CI = 8.4–20.2) hunting parties per hour at 0700 to 2.1 (95% CI = 1.2–3.9) at 1600 (Table S2). Temporal effects of hunting explained 17% of variation in hunting risk (R^2_{adj} = 0.165). Overall, we recorded 1,269 active hunting parties (i.e., presence of spinning-wing decoys) across surveys and hunting seasons. There were 2 hunting parties/km^2 across the entire surveyed area (range = 0–42) and 5 hunting parties/km^2 where hunting occurred (range = 1–42).

For spatial predictions, model performance was optimized for both hunting intensity and hunting variability when all covariates were included. For hunting intensity, tree depth ranged from 11–23 ($\bar{x}$ = 15) and the top contributing variables were blind density and surface water inundation frequency (variable importance [VI] = 4,098 [37%] and 1,887 [17%], respectively).

All other variables had VI scores ≤ 8%. Model performance based on validation data was reasonably accurate with a $\tilde{R}^2$ = 0.59 and a maximum R^2 = 0.74; the latter was used for spatial predictions (Fig. S1). The average out-of-bag RMSE = 2.1 which indicated that predictions could be off by ± 2 active hunting parties (i.e., spinning wing decoys).

Based on surveyor experience, spatial predictions of hunting intensity and variation were reasonably accurate. For example, high hunting intensity was predicted within the river channels of western Tennessee, near waterfowl sanctuaries[24], and on public and privately-hunted areas that are regionally-known to have no specified rest-days[4] (e.g., Open Lake Hunt Club, Reelfoot Lake, Gooch Wildlife Management Area [WMA]; Fig. S1).

2. Supplementary Context, Methods, Results

Appendix 2 – Survival and space-use of mallards that used and did not use sanctuary nodes during winter

Context

One hypothesis for the existence and benefit of waterfowl sanctuaries is they may increase winter survival, buffer against carry-over and possible cross-seasonal population effects that ultimately, enhance reproduction and recruitment. Limited evidence exists to quantify effects of sanctuary on winter survival and space-use of waterfowl because there are few marking and tracking studies where sanctuaries are not used or do not exist. There is limited evidence that establishing sanctuary may buffer against hunting mortality[25,26]. For example, Blohm et al. (1987)[27] provided some evidence for sanctuary buffering harvest mortality using multi-season autumn–winter banding efforts on and off sanctuary. Direct recovery rates following autumn banding were higher for male mallards (*Anas platyrhynchos*) banded off sanctuaries; they found

the same but a weaker pattern for female mallards. Nevertheless, annual survival rates ultimately did not differ between birds banded on and off sanctuaries[27]. Although they could only speculate[27], one mechanism for greater harvest of mallards banded off sanctuary could be that these ducks were disturbed more often, forced to relocate, and therefore increased daily or seasonal space-use thereby making them more susceptible to harvest.

We deployed hundreds of GPS transmitters on mallards but all deployments were within state or federal waterfowl sanctuary boundaries in western Tennessee. Most ducks used sanctuary following capture but 46 individuals never returned to sanctuary again. Thus, our data provided a unique opportunity to evaluate winter survival *and* space-use of "non-sanctuary" individuals compared to the much larger cohort of mallards that used sanctuary. In other words, we provide a measure of fitness (i.e., winter survival) that likely correlate and explain reduced transition probabilities by mallards within our sanctuary network.

Results of this supplemental analysis demonstrate: (1) an overwhelming majority of mallards (89.4%) and likely other waterfowl use sanctuary during winter; (2) overwintering survival increased with sanctuary use; and (3) daily and seasonal space-use differs among cohorts of mallards that do and do not use, or have access to sanctuary within the network. The latter is particularly important because mallards that never used sanctuary following capture had approximately two times greater nocturnal space-use compared to sanctuary users. This finding is likely a result of constant hunting disturbance off sanctuary that displaces individuals, thereby constricting range-sizes diurnally (Blake-Bradshaw 2024) and consequently necessitating exploratory behavior (i.e., flights or "transitions") nocturnally. Increased displacements likely degrade spatial memory and may be a mechanism for decreased fitness (i.e., increased harvest vulnerability). Acknowledging the small sample size of mallards that never used sanctuary

following capture, these supplemental results are suggestive that protected sanctuary networks promote overwintering survival.

Methods

For this analysis, we identified individuals that never used sanctuary across the 120-day winter period by intersecting locations with known waterfowl spatial sanctuary using the *sf* package[11,28]. We assigned a binary independent variable of sanctuary use to each individual where "0" denoted individuals that never used sanctuary following capture and "1" was the opposite. We estimated seasonal known-fate survival curves (i.e., Kaplan-Meir) and hazard ratios relative to binary sanctuary/non-sanctuary ducks by fitting a Cox proportional hazard model in the *survival* package[29,30]. We omitted the first 4 days following capture to ensure mallards acclimated to GPS-transmitters[31]. We right-censored individuals that did not die by the end of winter (i.e, 120 days from November–February) or stopped transmitting, assuming unbiased censoring[32,33]. We tested whether survival was different between sanctuary and non-sanctuary mallards using a log-rank χ^2 test at an *a priori* $\alpha = 0.05$[34]. Additionally, we report a seasonal baseline hazard ratio and survival probabilities at 30, 60, and 90 days for each GPS-marked cohort.

We fitted dynamic Brownian bridge movement models (dBBMMs) using package *move* to estimate daily and seasonal range sizes for sanctuary and non-sanctuary individuals[35]. We parameterized dBBMMs with 31 location window sizes, 11 location margins, and 23.5 m location error[36,37]. We used 50% and 95% contours (ha) to represent an individuals' core area and range size, respectively[38]. For both daily and seasonal core areas and range-sizes, we fitted separate linear mixed effects models in package *glmmTMB* with log-transformed 50 and 95% contours as response variables, a binary independent variable of sanctuary use or not (1 or 0), and specified each individual as a random intercept[39]. We tested for differences in space-use

between sanctuary and non-sanctuary mallards using a Type III Kenward-Roger *F* tests with an *a priori* statistical significance level at $\alpha = 0.1$. We tested main and interactive effects of sanctuary use (0 or 1) × time of day (day or night) for daily space-use and sanctuary use × season (pre-, hunting, and post-season) for seasonal winter space-use using Type III Kenward-Roger *F* tests that approximated residual degrees of freedom[40,41]. We selected Kenward-Roger *F* tests over others (*cf.* Satterthwaite), because this procedure minimized Type I error rates and is more robust to non-linear and correlated model structures[42,43]. We deemed statistical significance *a priori* at $\alpha = 0.1$.

Results

Sample sizes for these analyses slightly differed because we only used capture-year individuals, and because several daily range size calculations did not converge. Forty-six mallards never used sanctuary following capture and 397 used sanctuary at least once during the 120-day period. Seasonal survival time was greater for mallards that used sanctuary than those that did not ($P < 0.001$, $\chi^2 = 17.7$). Specifically, individuals that used sanctuary had 3.06 (95% CI = 1.77–5.31) times reduced hazard of death compared to individuals that did not use sanctuary. For 30 days, survival was 0.91 (95% CI = 0.88–0.94) and 0.72 (95% CI = 0.59–0.87) for mallards that used and did not use sanctuary, respectively. For 60 days, survival was 0.83 (95% CI = 0.77–0.87) and 0.55 (95% CI = 0.39–0.77) for individuals that used and did not use sanctuary, respectively. For 90 days, survival was 0.76 (95% CI = 0.71–0.82) and 0.54 (95% CI = 0.39–0.77) for individuals that used and did not use sanctuary (Fig. S2).

Daily winter core areas (i.e., 50% contour) between sanctuary and non-sanctuary mallards were similar during the day but differed at night ($F_{1,1.9e4} = 16.47$, $P < 0.001$). Specifically, sanctuary mallards used 10 ha (95% CI = 9–12 ha) during the day compared to 8 ha

(95% CI = 4–14) for non-sanctuary mallards. Conversely, sanctuary mallards used less than half the daily nighttime area (4 ha; 95% CI = 4–5 ha) than non-sanctuary mallards (11 ha; 7–17 ha). Non-sanctuary mallards' daily 95% ranges were also greater at night than during the day ($F_{1,1.9e4}$ = 3.47, P = 0.06). Sanctuary mallards used 114 ha (95% CI = 96–135 ha) during the day compared to 83 ha (95% CI = 44–154 ha) for non-sanctuary mallards. At night, non-sanctuary mallards used 1.2 times more area (128 ha; 95% CI = 79–209) than sanctuary mallards (100 ha; 84–119).

Seasonal winter core areas differed by sanctuary use or not ($F_{1,778}$ = 12.75, P < 0.001), season ($F_{2,699}$ = 6.79, P < 0.001), but these main effects did not covary ($F_{2,693}$ = 1.13, P = 0.322). Across winter, sanctuary ducks used 1.5 times more area (49 ha; 95% CI = 31 –78 ha) than non-sanctuary ducks (25 ha; 95% CI = 15–41 ha). Seasonal core areas increased from 19 ha (95% CI = 11 –31 ha) during pre-season to 30 ha (95% CI = 21–44 ha) during hunting season, and from 30 to 77 ha (95% CI = 51–117 ha) during post-season. This pattern was consistent for 95% winter ranges where main effects of sanctuary use and season differed ($F_{1,790}$ = 10.64, P = 0.001 and $F_{2,702}$ = 3.73, P = 0.001) but not their interaction. Sanctuary ducks used 2.3 times greater area (893 ha; 313–2,548 ha) than non-sanctuary ducks (396 ha; 95% CI = 177–887 ha). Range sizes increased 4.1 times from pre- to post-season; mallards used 314 ha (95% CI = 138–716 ha) during pre-season, 517 ha (218–1,224 ha) during hunting, and 1,293 ha (575–2910 ha) during post-season.

3. Supplementary Code

File S1. Attached JAGS text file for the parameterization of the multistate capture-recapture model to estimate sanctuary node transition probabilities relative to node emigration and

immigration sizes, distances among sanctuary nodes, and individual characteristics including age (juvenile, adult) and sex (male, female).

4. Supplementary Tables

Table S1. Attached large table (.xlsx) of system-specific sanctuary node transition probabilities (1–13). Sanctuary nodes included four National Wildlife Refuges (NWR) and seven state-owned waterfowl sanctuaries including Big Lake National Wildlife Refuge (BLNWR) in Arkansas, Reelfoot Lake NWR north unit (RLNWR_N) in Kentucky and Tennessee, and Reelfoot Lake NWR south unit (RLNWR_S), Lake Isom NWR (LINWR), Chickasaw NWR in Tennessee and Lake Lauderdale (LL), Horns Bluff (HB), White Lake (WL), Bean Switch (BS), Maness Swamp (M), Hop-in (HI), Black Bayou (BB), and Phillipy Waterfowl Refuges (P).

Table S2. Summary table for the supplementary analysis predicting the number of active hunting parties per hour (log-transformed) across aerial surveys 2019–2022 in western Tennessee, USA relative to time-varying predictors including Year (indicator variable = First Year), weekday versus weekend (indicator = weekday), hour of the day, week of the year, and the interaction between hour and week. The summary table depicts parameter estimates (β), standard error (SE), critical value (*t*), and *P*-values. Bolded *P*-values are statistically significant. Of importance to the referenced manuscript: (1) Only hour of the day influenced active hunting and thus landscape-level hunting pressure, which we anticipated *a priori* and thus, rotated the beginning geographic strata per survey to obtain a representative sample of hunting across the entire landscape; and (2) active hunting parties were not affected by any other temporal variables which justified pooling

observations across days, weeks, and years for the random forest model that predicted spatial intensity of hunting (Fig. S1).

	ln(β)	SE	*t*-value	*P*-value
Intercept	4.800	1.022	4.695	**7.0e-6**
Second Year	-0.243	0.202	-1.203	0.230
Third Year	-0.084	0.216	-0.391	0.697
Weekend	0.049	0.178	0.273	0.785
Hour	-0.298	0.095	-3.128	**0.002**
Week	-0.164	0.190	-0.862	0.390
Hour:Week	0.019	0.018	1.101	0.273

Table S3. State transition matrix for our multistate model to estimate daily movement transition probabilities of mallards (*Anas platyrhynchos*) among protected sanctuary areas managed for waterfowl and other wetland-dependent wildlife during autumn –winter in western Tennessee and Kentucky and eastern Arkansas and Missouri. Sanctuary node "states" included: Sanctuary node "states" included: Black Bayou Refuge (BB), Lake Isom National Wildlife Refuge (LINWR), Bean Switch Refuge (BS), Maness Swamp Refuge (M), White Lake Refuge (WL), Chickasaw (CNWR), Big Lake (BLNWR), Lake Lauderdale Refuge (LL), Reelfoot Lake North (RFNWR North), Horns Bluff (HB), Reelfoot Lake South (RLNWR South), Phillipy Refuge (P), and Dead or lost bird and/or transmitter.

	BB	LINWR	BS	HI	M	WL	CNWR	BLNWR	LL	RLNWR North	HB	RLNWR South	P	Dead or lost
BB	$\phi(1-\sum_{j=1}^{j=12}\psi_{BB::j})^{A}$	$\phi\psi_{BB::LI}$	$\phi\psi_{BB::BS}$	$\phi\psi_{BB::HI}$	$\phi\psi_{BB::M}$	$\phi\psi_{BB::WL}$	$\phi\psi_{BB::C}$	$\phi\psi_{BB::BL}$	$\phi\psi_{BB::LL}$	$\phi\psi_{BB::RL-N}$	$\phi\psi_{BB::HB}$	$\phi\psi_{BB::RL-S}$	$\phi\psi_{BB::P}$	$1-\phi$
LINWR	$\phi\psi_{LI::BB}$	$\phi(1-\sum_{j=1}^{j=12}\psi_{LI::j})^{A}$	$\phi\psi_{LI::BS}$	$\phi\psi_{LI::HI}$	$\phi\psi_{LI::M}$	$\phi\psi_{LI::WL}$	$\phi\psi_{LI::C}$	$\phi\psi_{LI::BL}$	$\phi\psi_{LI::LL}$	$\phi\psi_{LI::RL-N}$	$\phi\psi_{LI::HB}$	$\phi\psi_{LI::RL-S}$	$\phi\psi_{LI::P}$	$1-\phi$
BS	$\phi\psi_{BS::BB}$	$\phi\psi_{BS::LI}$	$\phi(1-\sum_{j=1}^{j=12}\psi_{BS::j})^{A}$	$\phi\psi_{BS::HI}$	$\phi\psi_{BS::M}$	$\phi\psi_{BS::WL}$	$\phi\psi_{BS::C}$	$\phi\psi_{BS::BL}$	$\phi\psi_{BS::LL}$	$\phi\psi_{BS::RL-N}$	$\phi\psi_{BS::HB}$	$\phi\psi_{BS::RL-S}$	$\phi\psi_{BS::P}$	$1-\phi$
HI	$\phi\psi_{HI::BB}$	$\phi\psi_{HI::LI}$	$\phi\psi_{HI::BS}$	$\phi(1-\sum_{j=1}^{j=12}\psi_{HI::j})^{A}$	$\phi\psi_{HI::M}$	$\phi\psi_{HI::WL}$	$\phi\psi_{HI::C}$	$\phi\psi_{HI::BL}$	$\phi\psi_{HI::LL}$	$\phi\psi_{HI::RL-N}$	$\phi\psi_{HI::HB}$	$\phi\psi_{HI::RL-S}$	$\phi\psi_{HI::P}$	$1-\phi$
M	$\phi\psi_{M::BB}$	$\phi\psi_{M::LI}$	$\phi\psi_{M::BS}$	$\phi\psi_{M::HI}$	$\phi(1-\sum_{j=1}^{j=12}\psi_{M::j})^{A}$	$\phi\psi_{M::WL}$	$\phi\psi_{M::C}$	$\phi\psi_{M::BL}$	$\phi\psi_{M::LL}$	$\phi\psi_{M::RL-N}$	$\phi\psi_{M::HB}$	$\phi\psi_{M::RL-S}$	$\phi\psi_{M::P}$	$1-\phi$
WL	$\phi\psi_{WL::BB}$	$\phi\psi_{WL::LI}$	$\phi\psi_{WL::BS}$	$\phi\psi_{WL::HI}$	$\phi\psi_{WL::M}$	$\phi(1-\sum_{j=1}^{j=12}\psi_{WL::j})^{A}$	$\phi\psi_{WL::C}$	$\phi\psi_{WL::BL}$	$\phi\psi_{WL::LL}$	$\phi\psi_{WL::RL-N}$	$\phi\psi_{WL::HB}$	$\phi\psi_{WL::RL-S}$	$\phi\psi_{WL::P}$	$1-\phi$
CNWR	$\phi\psi_{C::BB}$	$\phi\psi_{C::LI}$	$\phi\psi_{C::BS}$	$\phi\psi_{C::HI}$	$\phi\psi_{C::M}$	$\phi\psi_{C::WL}$	$\phi(1-\sum_{j=1}^{j=12}\psi_{C::j})^{A}$	$\phi\psi_{C::BL}$	$\phi\psi_{C::LL}$	$\phi\psi_{C::RL-N}$	$\phi\psi_{C::HB}$	$\phi\psi_{C::RL-S}$	$\phi\psi_{C::P}$	$1-\phi$
BLNWR	$\phi\psi_{BL::BB}$	$\phi\psi_{BL::LI}$	$\phi\psi_{BL::BS}$	$\phi\psi_{BL::HI}$	$\phi\psi_{BL::M}$	$\phi\psi_{BL::WL}$	$\phi\psi_{BL::C}$	$\phi(1-\sum_{j=1}^{j=12}\psi_{BL::j})^{A}$	$\phi\psi_{BL::LL}$	$\phi\psi_{BL::RL-N}$	$\phi\psi_{BL::HB}$	$\phi\psi_{BL::RL-S}$	$\phi\psi_{BL::P}$	$1-\phi$
LL	$\phi\psi_{LL::BB}$	$\phi\psi_{LL::LI}$	$\phi\psi_{LL::BS}$	$\phi\psi_{LL::HI}$	$\phi\psi_{LL::M}$	$\phi\psi_{LL::WL}$	$\phi\psi_{LL::C}$	$\phi\psi_{LL::BL}$	$\phi(1-\sum_{j=1}^{j=12}\psi_{LL::j})^{A}$	$\phi\psi_{LL::RL-N}$	$\phi\psi_{LL::HB}$	$\phi\psi_{LL::RL-S}$	$\phi\psi_{LL::P}$	$1-\phi$
RLNWR North	$\phi\psi_{RL-N::BB}$	$\phi\psi_{RL-N::LI}$	$\phi\psi_{RL-N::BS}$	$\phi\psi_{RL-N::HI}$	$\phi\psi_{RL-N::M}$	$\phi\psi_{RL-N::WL}$	$\phi\psi_{RL-N::C}$	$\phi\psi_{RL-N::BL}$	$\phi\psi_{RL-N::LL}$	$\phi(1-\sum_{j=1}^{j=12}\psi_{RL-N::j})^{A}$	$\phi\psi_{RL-N::HB}$	$\phi\psi_{RL-N::RL-S}$	$\phi\psi_{RL-N::P}$	$1-\phi$
HB	$\phi\psi_{HB::BB}$	$\phi\psi_{HB::LI}$	$\phi\psi_{HB::BS}$	$\phi\psi_{HB::HI}$	$\phi\psi_{HB::M}$	$\phi\psi_{HB::WL}$	$\phi\psi_{HB::C}$	$\phi\psi_{HB::BL}$	$\phi\psi_{HB::LL}$	$\phi\psi_{HB::RL-N}$	$\phi(1-\sum_{j=1}^{j=12}\psi_{HB::j})^{A}$	$\phi\psi_{HB::RL-S}$	$\phi\psi_{HB::P}$	$1-\phi$
RLNWR South	$\phi\psi_{RL-S::BB}$	$\phi\psi_{RL-S::LI}$	$\phi\psi_{RL-S::BS}$	$\phi\psi_{RL-S::HI}$	$\phi\psi_{RL-S::M}$	$\phi\psi_{RL-S::WL}$	$\phi\psi_{RL-S::C}$	$\phi\psi_{RL-S::BL}$	$\phi\psi_{RL-S::LL}$	$\phi\psi_{RL-S::RL-N}$	$\phi\psi_{RL-S::HB}$	$\phi(1-\sum_{j=1}^{j=12}\psi_{RL-S::j})^{A}$	$\phi\psi_{RL-S::P}$	$1-\phi$
P	$\phi\psi_{P::BB}$	$\phi\psi_{P::LI}$	$\phi\psi_{P::BS}$	$\phi\psi_{P::HI}$	$\phi\psi_{P::M}$	$\phi\psi_{P::WL}$	$\phi\psi_{P::C}$	$\phi\psi_{P::BL}$	$\phi\psi_{P::LL}$	$\phi\psi_{P::RL-N}$	$\phi\psi_{P::HB}$	$\phi\psi_{P::RL-S}$	$\phi(1-\sum_{j=1}^{j=12}\psi_{P::j})^{A}$	$1-\phi$
Dead or lost	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Table S4. Observation matrix of true and observed states for our multistate model to estimate daily movement transition probabilities of mallards (*Anas platyrhynchos*) among protected sanctuary areas managed for waterfowl and other wetland-dependent wildlife during autumn –winter in western Tennessee and Kentucky and eastern Arkansas and Missouri. Sanctuary node "states" included: Black Bayou Refuge (BB), Lake Isom National Wildlife Refuge (LINWR), Bean Switch Refuge (BS), Maness Swamp Refuge (M), White Lake Refuge (WL), Chickasaw (CNWR), Big Lake (BLNWR), Lake Lauderdale Refuge (LL), Reelfoot Lake North (RFNWR North), Horns Bluff (HB), Reelfoot Lake South (RLNWR South), Phillipy Refuge (P), and Dead or lost bird and/or transmitter.

	BB	LINWR	BS	HI	M	WL	CNWR	BLNWR	LL	RLNWR North	HB	RLNWR South	P	Dead or lost
BB	p	0	0	0	0	0	0	0	0	0	0	0	0	$1-p$
LINWR	0	p	0	0	0	0	0	0	0	0	0	0	0	$1-p$
BS	0	0	p	0	0	0	0	0	0	0	0	0	0	$1-p$
HI	0	0	0	p	0	0	0	0	0	0	0	0	0	$1-p$
M	0	0	0	0	p	0	0	0	0	0	0	0	0	$1-p$
WL	0	0	0	0	0	p	0	0	0	0	0	0	0	$1-p$
CNWR	0	0	0	0	0	0	p	0	0	0	0	0	0	$1-p$
BLNWR	0	0	0	0	0	0	0	p	0	0	0	0	0	$1-p$
LL	0	0	0	0	0	0	0	0	p	0	0	0	0	$1-p$
RLNWR North	0	0	0	0	0	0	0	0	0	p	0	0	0	$1-p$
HB	0	0	0	0	0	0	0	0	0	0	p	0	0	$1-p$
RLNWR South	0	0	0	0	0	0	0	0	0	0	0	p	0	$1-p$
P	0	0	0	0	0	0	0	0	0	0	0	0	p	$1-p$
Dead or lost	0	0	0	0	0	0	0	0	0	0	0	0	0	1

5. Supplementary Figures

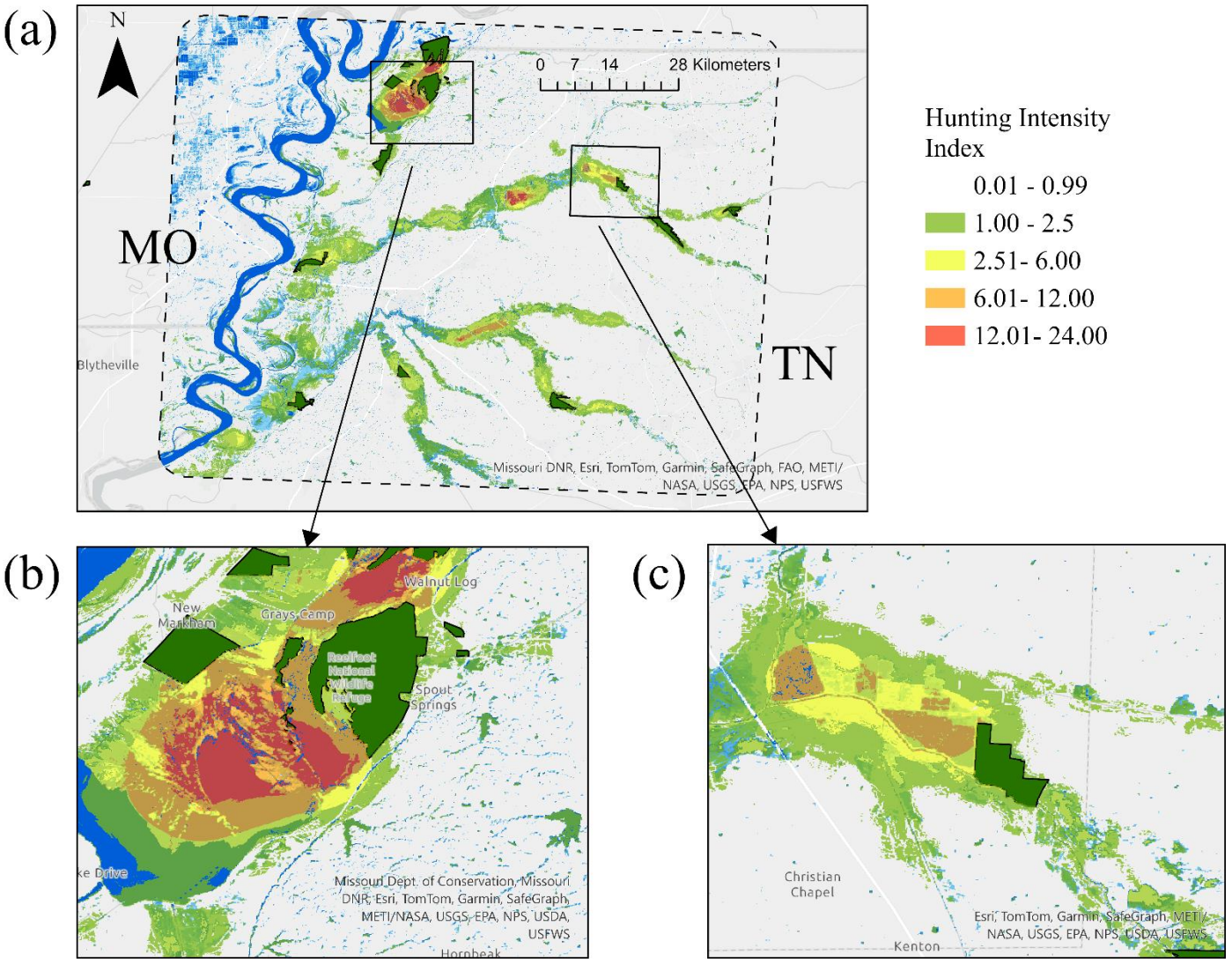

Figure S1. Spatial predictions from random forest analysis of landscape-level hunting intensity in western Tennessee and a small portion of northeastern Arkansas (a) based on mean aerial observations of active hunting parties (green to red) across winters 2019 through 2022. Hunting intensity indicies (i.e., number of active hunting parties) is masked < 1. The gradient of blue illustrates available wetland habitat for mallards, where light-dark blue illustrates the gradient of seasonal-permanent wetlands (Masto et al. 2024). Examples of intense hunting surrounding

sanctuary nodes are illustrated on Reelfoot Lake, Lake County, Tennessee, USA (b) and Davy Crocket Hunting Club, Crockett County, Tennessee, USA (c). Dark green areas with the floodplain outlined in black are state and federal waterfowl spatial sanctuaries. Map colors are segmented by a data-driven geometric interval with 5 categories for visual interpretation. Spatial predictions of hunting pressure illustrate the "inhospitable" landscape matrix that justify our use of sanctuary nodes as islands of suitable habitat patches diurnally.

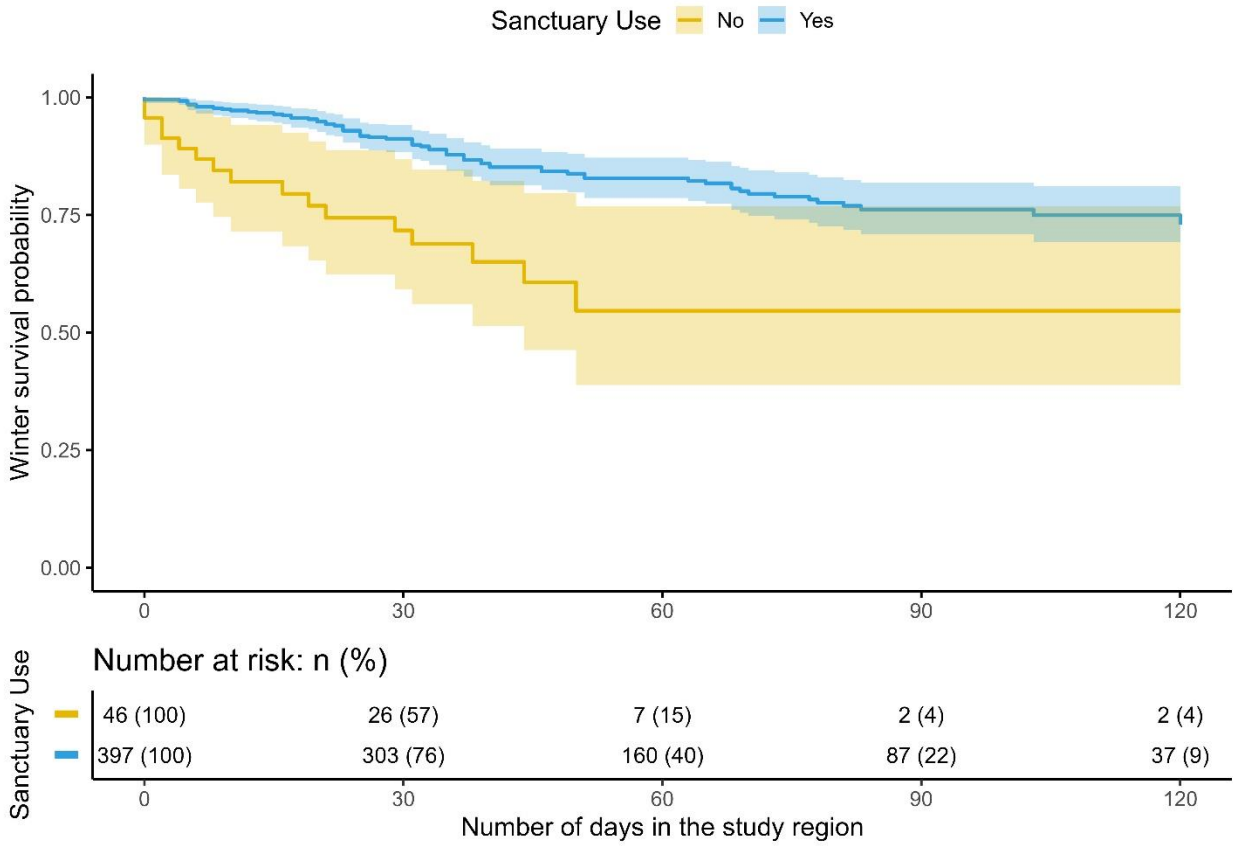

Figure S2. Kaplan-Meier seasonal survival and 95% confidence intervals during the 120-day winter period (November–February) for mallards captured in Tennessee, USA from 2019–2022 that used (blue) and did not use (yellow) protected waterfowl sanctuary following capture, GPS-marking, and release. Survival curves are accompanied by associated risk table illustrating the number and percentage of individuals throughout the study period.

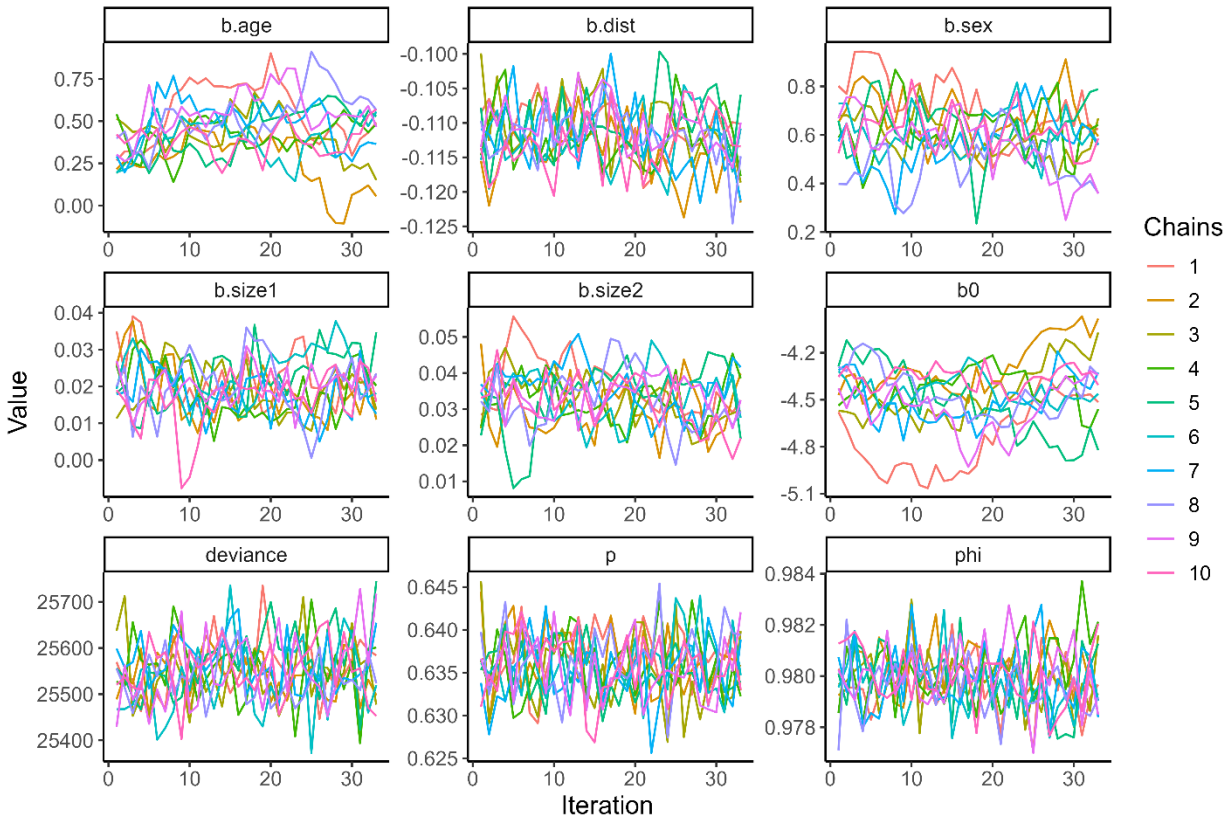

Figure S3. MCMC simulation traceplots across all multistate model parameters including age and sex of individuals (b.age and b.sex, respectively), proximity between sanctuary nodes (b.dist), size of immigration and emigration sanctuaries (b.size1 and b.size2, respectively), intercept (b0), deviance, recapture probability across all sanctuaries (p), and survival probability of the animal or transmitter (phi).

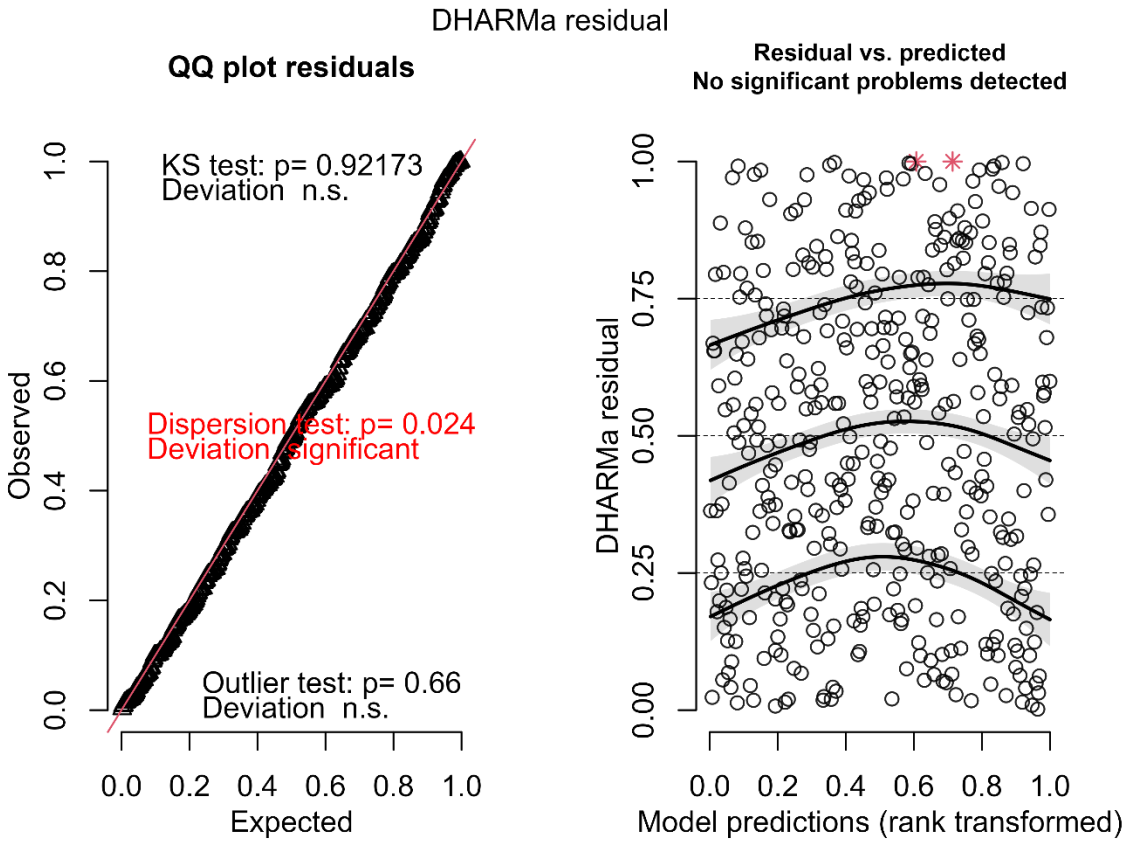

Figure S4. QQ plot and simulated scaled residuals based on the fitted generalized linear model with a truncated error distribution for sanctuary use. Diagnostic plots and statistical tests for overdispersion, influential outliers, and goodness-of-fit demonstrate overall reasonable model fit with no severe violation of model assumptions.

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