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RESEARCH ARTICLE

Data integration reveals that a statewide corridor initiative maintains greater wild turkey relative abundance and occupancy

Muzi D. Sibiya · Brittany M. Mason · Carolina Baruzzi · Diana E. Bowler · Marcus A. Lashley · Corey T. Callaghan

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Abstract

Context Wildlife corridors have been proposed to strategically conserve wildlife habitat such that it facilitates connectivity between populations to allow dispersal, geneflow, and species migrations as the climate changes. However, few empirical examples have demonstrated the effectiveness of landscape-scale wildlife corridors. The Florida Wildlife Corridor (FLWC) includes 7.3 million hectares of connected undeveloped lands in Florida, USA, offering a real-world opportunity to assess the effectiveness of a landscape-scale corridor amid rapid development.

Objectives Our objective was to evaluate how land cover and human population density influence wild turkey predicted occupancy and relative abundance. We then applied those relationships to predict how turkey populations differ inside and outside the Florida Wildlife Corridor (FLWC). Specifically, we compared the spatial differences in predicted occupancy and relative abundance to infer the potential role of the FLWC in supporting turkey populations under current landscape conditions.

Methods We first estimated the effects of land cover variables, climate, and human population density on wild turkey occupancy and relative abundance by integrating presence, count, and detection/non-detection data from citizen science and agency sources using hierarchical occupancy and spatially explicit integrated models. We used these modeled relationships to predict turkey distribution (i.e., occupancy and relative abundance) statewide and compared these variables inside and outside the FLWC. Additionally, we compared observed productivity inside and outside the FLWC.

Results Overall, the predicted occupancy and relative abundance were higher inside the FLWC compared to outside. Both predicted occupancy and relative abundance tended to decrease with urbanization and human population. Importantly, natural landcovers, including forests, shrublands, and grasslands, were predominantly located inside the FLWC,

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M. D. Sibiya · B. M. Mason · C. T. Callaghan (✉)
Department of Wildlife Ecology and Conservation, Fort Lauderdale Research and Education Center, Institute of Food and Agricultural Sciences, University of Florida, Davie, FL, USA
e-mail: c.callaghan@ufl.edu

C. Baruzzi
Department of Wildlife Ecology and Conservation, North Florida Research and Education Center, University of Florida, Quincy, FL, USA

D. E. Bowler
Biodiversity Monitoring & Analysis, UK Centre for Ecology & Hydrology, Wallingford, UK

M. A. Lashley
Department of Wildlife Ecology and Conservation, University of Florida, Gainesville, FL, USA

whereas open water, agricultural, and higher human population densities were concentrated outside the corridor. Observed productivity was similar inside and outside the FLWC.

Conclusions Given that measures of turkey population productivity did not vary within and outside the FLWC, we speculate that the observed patterns may reflect indirect benefits of connectivity rather than direct effects on reproduction. For example, improved habitat availability or quality, movement opportunities, or other effects that moderate survival (e.g., predator differences) may be underlying mechanisms behind the difference between inside and outside the FLWC. Nevertheless, given the observed differences in relative abundance and occupancy, our findings support the growing recognition of the importance of maintaining habitat connectivity for conservation of wildlife in the face of global change.

Keywords Distribution · Habitat connectivity · Occupancy · Population · Wild turkey *Meleagris gallopavo*

Introduction

Habitat loss remains a major driver of global species loss (Young et al. 2016; Fahrig et al. 2019; Jaureguiberry et al. 2022). Anthropogenic pressures stemming from habitat loss manifest in various ways but commonly result in fragmentation of existing habitat patches (Young et al. 2016; Masson-Delmotte et al. 2021). Intact natural areas are critical for species conservation to sustain sufficiently large and viable populations and their resources (Wilson et al. 2016; Plumptre et al. 2021). Habitat connectivity – which is a measure of how landscapes allow for the dispersal of organisms (Taylor et al. 1999) – ensures that species can move between habitat patches, supporting critical ecological processes such as gene flow (Sawaya et al. 2014), resource access, and thus increasing population resilience. Enhancing and maintaining habitat connectivity can improve functional connectivity (Tischendorf and Fahrig 2000) and conservation outcomes in the face of ongoing anthropogenic changes.

A common technique to increase and maintain habitat connectivity is the development of habitat connectivity networks. These networks, often referred to as ecological or wildlife corridors, are broadly defined as a deliberate effort to establish or conserve usable space that connects isolated habitat patches to facilitate wildlife movement, dispersal, and geneflow (Tewksbury et al. 2002; Brodie et al. 2025). Wildlife corridors are a key strategy to enhance habitat connectivity with a goal to link fragmented habitats, often surrounded by anthropogenically altered landscapes (Fletcher et al. 2016; Gregory et al. 2021; Wang et al. 2023). While habitat networks and wildlife corridors are increasingly promoted as a priority conservation strategy (MacDonald 2003; DeFries et al. 2023), their effectiveness in biodiversity conservation requires empirical evaluation in most systems. Efforts to understand functional connectivity mostly rely on animal movement behavior (Naidoo et al. 2018), but such data are often logistically difficult to collect and collate. In contrast, distribution and demographic data (e.g., occupancy, relative abundance, and productivity) can provide landscape-scale indicators of functional connectivity when compared inside and outside connectivity patches. These data reveal where populations exist and survive across heterogeneous environment and there is a growing number of studies that incorporate occurrence and/or abundance data (e.g.,Thapa et al. 2017; Iverson et al. 2024) to assess the efficacy of wildlife corridors. Yet, data that allows the assessment of the role of wildlife corridors on conservation outcomes is often limited in availability and/or spatial extent. There is also a notable gap in taxa representation within empirical field studies on connectivity, with most studies focusing on mammals (Wallace et al. 2020; Naidoo et al. 2018; Thapa et al. 2017; Letro et al. 2022; Leskova et al. 2022; Dixon et al. 2006), meaning that the evidence for other taxa is weak. Filling this gap is crucial to fully understanding and optimizing the role of wildlife corridors in biodiversity conservation.

In North America and across the southeastern United States (US), the role of wildlife corridors is important because of the increased potential to reduce the effects of anthropogenic climatic and environmental changes on wildlife (McGuire et al. 2016). For example, in addition to climatic threats associated with sea-level rise and flooding, Florida is experiencing a relatively rapid land use change in the form of urbanization and agricultural expansion, especially in the southern half of the state (Leskova et al. 2022; Daskin et al. 2024). These pressures have highlighted the need for development of effective wildlife corridors to facilitate species movement and population resilience. While narrow corridors are the classical focus of connectivity studies (e.g., Gilbert-Norton et al. 2010), large-scale conservation initiatives combine extensive habitat cores with narrow linkages, creating mosaic landscapes of conservation value. The Florida Wildlife Corridor (FLWC), a statewide network of ~ 18 million acres (72,843 km^2) or 43% of the state exemplifies this approach. The FLWC Act was signed into law in 2021, and its main mission is "*To champion a collaborative campaign to permanently connect, protect and restore the Florida Wildlife Corridor*" (The Florida Wildlife Corridor Act 2021; Florida Wildlife Corridor 2024). Parcels of land are continuously added to the FLWC such that an additional 82,000 ha have been incorporated into the FLWC since 2021 (Daskin et al. 2024). The effectiveness of the FLWC on species of conservation concern remains largely unknown, providing a valuable case study to test the importance of habitat connectivity for wildlife.

Recent analyses indicate declines in wild turkey (*Meleagris gallopavo*) populations across their range, potentially accelerating in recent years (Byrne et al. 2016; Parent et al. 2016). Wild turkey habitat requirements vary seasonally, but it is especially critical to understand the species' habitat requirements during the breeding season. Reproductive success is particularly dependent on frequent disturbance maintaining the vegetation structure that supports nesting and brood (poult) use, but is also influenced by climatic factors (Boone et al. 2023, 2024; Nelson et al. 2023). Moreover, there is evidence for adult female mortality during the nesting (Tyl et al. 2023) and/or brooding stage driven by a mixture of anthropogenic impacts, loss of vegetation structure (Turner et al. *unpublished results*), and density-dependant factors (Chamberlain et al. 2020). At both the local and landscape scale, vegetation heterogeneity and early succession habitat (i.e., open patches), respectively, are selected by brood rearing females (Streich et al. 2015; Bowling et al. 2015; Chamberlain et al. 2020; Pollentier et al. 2017). At local scales, ground cover often characterized by a mixture of forbs or grasses, provide suitable foraging ground while facilitating poult movement, providing cover from predators, and minimizing thermal stress (Dickson 1992). Dynamics of the species' occurrence, population abundance, and productivity at broad scales and within the context of designated wildlife corridors, are less explored. Studies suggests that wild turkey distribution is discontinous (e.g., Pollentier et al. 2021), juvenile and adult female turkeys predominantly drive dispersal (Thogmartin and Schaeffer 2000; Watkins 2022), and that habitat loss increases dispersal distances (Marable et al. 2012), which can negatively affect fitness. As such, the FLWC may play a vital role in promoting wild turkey populations, by allowing dispersal and gene flow.

We combined citizen science and state agency data, to model wild turkey distribution, abundance, and reproductive success across the state of Florida. We then used these modelled predictions to evaluate the contribution of the FLWC. To do this, we first analysed the relationships between environmental covariates and species occupancy and relative abundance. Next, we used the fitted models to predict the distribution of the species across Florida. Finally, we used these predictions to compare species occupancy, relative abundance, and productivity inside and outisde the wildlife corridor. A secondary goal was to assess differences in occupancy and relative abundance among the two subspecies of wild turkey found throughout Florida. Our findings add to the evidence-base for the development of wildlife corridors for biodiversity conservation.

Methods

Study area

Our study is based in Florida and evaluates the impact of the FLWC based on geographic delineation described in the FLWC Act of 2021 (The Florida Wildlife Corridor Act 2021; Fig. 1). Initial attempts to develop the FLWC were spearheaded by the Florida Ecological Greenways Network (FEGN) (Hoctor et al. 2000). There are several reasons to prioritize evaluation of ecological responses to the FLWC. First, the state's natural landscapes continue to be converted to urban and agricultural landscapes, both inside and outside the FLWC (Daskin et al. 2024). Second, approximately half (~ 9.6 million acres) of the ~ 18 million acres of the FLWC is currently managed as conservation areas and the rest remains unprotected, despite being potentially critical for biodiversity conservation (Jenkins et al. 2015). The FEGN labeled

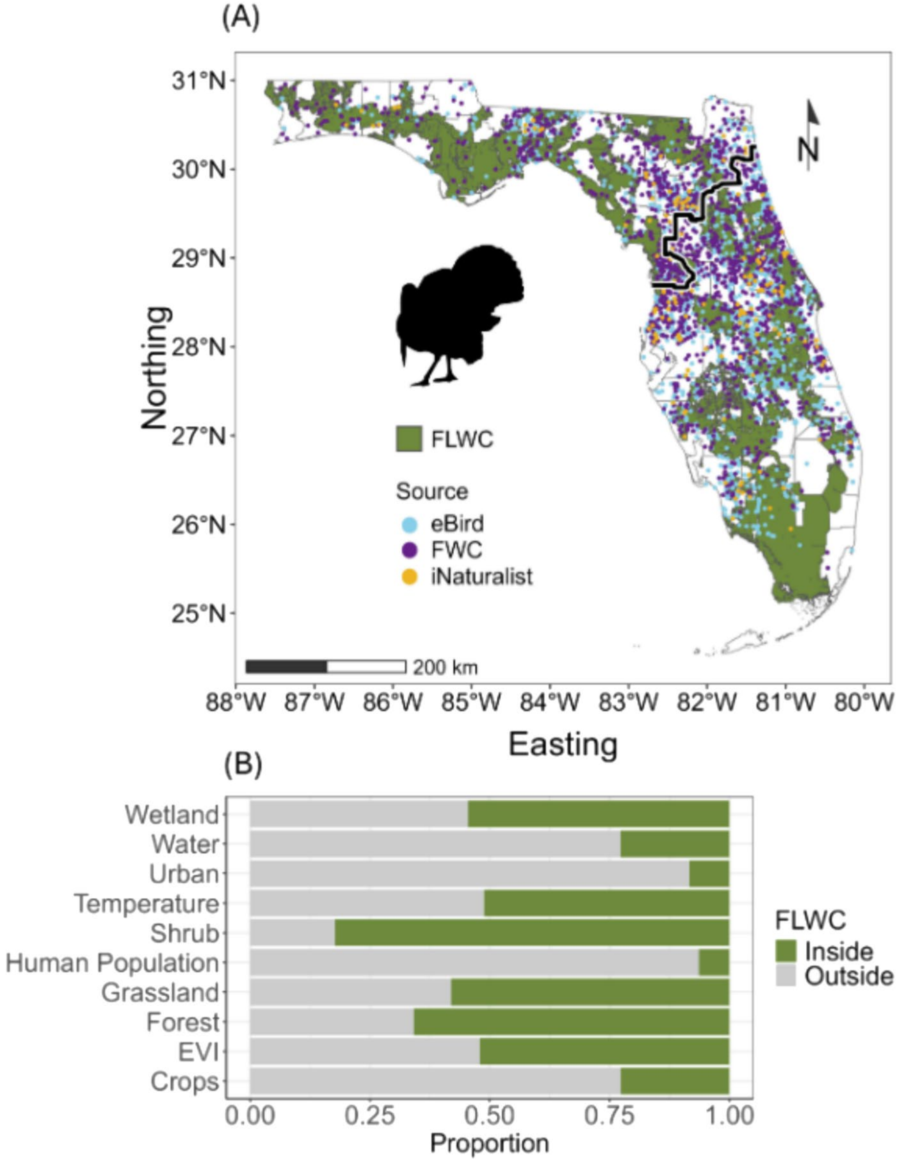

Fig. 1 **A** Map showing the Florida Wildlife Corridor (FLWC) and a random selection of a quarter of locations where wild turkeys were observed from eBird and Florida Fish and Wildlife Conservation Commission (FWC) including all iNaturalist observations during the brooding season (June–August) between 2020 and 2023. The black line represents the regional separation of Eastern wild turkey (north/northwest of line) and Osceola wild turkey (south of line). subspecies. **B** The bar graph shows variation in the amount of land cover and human population inside compared to outside the FLWC. Turkey brood-rearing important natural vegetation attributes (forests, shrublands and grasslands) are dominant inside the FLWC whereas human population including developed landscapes (urban and cropland) are extensive outside

these unprotected landscapes as ‘Opportunity Areas’, in recognition of their conservation value and critical role in facilitating contiguity of natural landscapes. Finally, FEGN continues to develop the FLWC and requires additional information, including on the status of wildlife species, to increase the predictive power of their habitat connectivity models.

Florida contains two wild turkey subspecies, the Eastern wild turkey (*M. g. silvestris*) and the Osceola wild turkey (*M. g. osceola*), but these are not separated in the raw observations (i.e., rarely do citizen science participants specify subspecies status). Instead, we used geographic boundaries. The Eastern Wild Turkey is dominant in the northern part of the state whereas Osceola occupies the peninsula Florida (Chamberlain et al. 2022). Therefore, we designated the Northwest and North Central as Eastern wild turkey range whereas Northeast, Southwest, and South represented Osceola wild turkey range within Florida (Fig. S1). While the state-delineated management regions are like those of the accepted range delineation of subspecies, we acknowledge they do not match precisely.

Data collation and sorting

We aggregated and integrated three data types including counts, presence-only and presence-non-detection observations from Florida Fish and Wildlife Conservation Commission (FWC), iNaturalist, and eBird, respectively, between 2020 and 2023. While the three data sets comprise observations from across the state, their spatiotemporal coverage, size, and observational bias vary and therefore we expect that their joint modeling will produce more robust wild turkey distribution estimates. We focused on data collected when wild turkeys could be observed with poults from June to August. Normally in Florida wild turkeys begin laying their eggs around early April, with a clutch size between 9 and 12 eggs, they take on average 12 to 13 days to finish laying eggs. Incubation on the other hand lasts between 26–28 days and that means April is generally for laying eggs, May is for incubation, and June is when poults hatch.

eBird's presence and non-detection observations

We retrieved wild turkey observations (presence points) and sampling event information (with no wild turkey observations) from eBird (www.ebird.org). The eBird patform was developed by the Cornell Lab of Ornithology in 2002 (Sullivan et al. 2009). It is a semi-structured citizen science data program that allows for specifying whether an observer submitted a complete checklist or not. Complete checklists have been used to inform models built under the presence-non-detection paradigm (e.g., Ramesh et al. 2022). Specifically, complete checklists provide means to estimate species detection probability (Johnston et al. 2021). We followed eBird's best practices (Johnston et al. 2021) to minimize some of the known biases within eBird observations. Specifically, we selected checklists (i) submitted by < 10 observers per checklist, (ii) limited duration to < 300 min and (iii) from stationary or effort distance < 5 km. Furthermore, we attempted to limit the impacts of spatio-temporal bias in observations by subsampling data within 5 km hexagon grids across the state. Zero-filled eBird data often suffers from class imbalance, for instance, non-detections tend to dominate the records; to minimize the effects of class imbalance (Steen et al. 2021), we subsampled the non-detections (Ramesh et al. 2022), by drawing a single random point from each 5 km hexagon cell per month during the four years before combining the non-detection data with the presence points. The eBird dataset contained 98,202 observations, of which 1687 were presence points and 96,507 were absence points. Subsampling reduced the absence dataset to 13,691.

Florida Fish and Wildlife Conservation Commission (FWC) counts and productivity data

FWC's brood surveys provide valuable information regarding wild turkey productivity. Agency employees and private citizens contributed geo-referenced wild turkey counts. Whenever possible, observers also provide demographic information by specifying the number of gobblers, hens, and poults. We excluded data points without geographic information, points that fell outside the state boundary such as those falling within the ocean, and obviously aberrant data. To minimize double counting, the data collection protocol also encouraged participants to indicate whether they believed they had seen a wild turkey group before (yes or no) in a particular location and based on this information, we excluded records when an observer responded 'Yes'. To further minimize potential bias in observations, we established 5 km hexagons across the state and randomly selected a single sample per hexagon cell per month. The FWC dataset contained 12,281 observations. We removed 329 observations as part of data cleaning. We additionally removed 21.6% of the data (N = 2585) where the observer believed they had observed the same turkey in the past. Finally, subsampling resulted in the removal of 3409 observations. In all, 5958 FWC observations were included in analysis.

iNaturalist's presence points

We retrieved presence-only observation data from iNaturalist (www.inaturalist.org), which is a platform for assembling citizen biodiversity observations of various taxa. To share an observation, iNaturalist participants upload photographs or audio, along with the location, date, time, and an initial identification of the organism. To obtain 'Research Grade' status, an observation must have more than two-thirds agreement on species identification from the community. For this study, we obtained all wild turkey observations classified as 'Research Grade' between June and August from 2020 to 2023 via GBIF (GBIF.org 2023). Similar to FWC datasets, we cleaned iNaturalist observations by removing points with inaccurate geographic location (observation accuracy measures ≥ 1 km). We then spatially subsampled the data by dividing the state into 5 km hexagonal grid cells and randomly selecting one observation per cell per month. The iNaturalist dataset contained 202 wild turkey observations. This filtering process removed 20 observations, resulting in a final dataset of 182 observations included in the analysis.

Covariates

To quantify variability in wild turkey occurrence and relative abundance in relation to the FLWC, we first examined variability in wild turkey occurrence and relative abundance throughout Florida. We utilized landcover covariates from the National Land Cover Data (NLCD) of 2021 (Dewitz 2023), human population density from the Gridded Population of the World data set (Center for International Earth Science Information Network 2018), vegetation greenness (enhanced vegetation index (EVI)) computed from the Landsat data (LANDSAT/LC08/C02/T1_TOA) repository (USGS 2021), and annual mean temperature from WorldClim, at 30 s or ~ 1km^2 (Fick and Hijmans 2017; Table S1). We reclassified the NLCD into seven classes, based on our understanding of wild turkey biology: water (open water bodies), developed (including cities/urban areas and other built land cover classes), grassland (combined pastures and open ground land cover classes), forest (combined all tree cover land classes), shrub, crops (agriculture), and wetland vegetation. Due to the high variability of wetlands in Florida, where some are wet year-around and others dry down for portions of the year, we incorporated elevation (Danielson and Gesch 2011) into the wetland land cover layer. Therefore, this raster layer assigns a value of 0 to all locations without wetlands, and a continuous elevation value to locations where wetlands are present. To predict the effects of general vegetation greenness, we computed the enhanced vegetation index (EVI) based on Landsat 8 images taken by the operational land imager (OLI) sensor filtered to 2022. Specifically, we used the formula: 2.5 x ((B5—B4) / (B5 + 6 × B4—7.5 × B2 + 1)), to compute EVI following Landsat 8 data extraction protocols. Landsat 8 and OLI sensor images have a 30 m resolution and with a 16-day repeat cycle, computation of the monthly EVI index is possible. Furthermore, we extracted human population density from the Gridded Population of the World (GPW) database. The GPW version 4.1.1 was released in July 2021 and modified in February 2022. Human population density is estimated based on ~ 1 × 1 km grid cells across the globe. All data – landcover, EVI computation, and GPW – were clipped to Florida in the Google Earth Engine platform (GEE) (Gorelick et al. 2017). Landcover reclassification was carried out in R (version 4.4.0) using the *reclassify* function of the raster package (Hijmans 2025). We created a landcover, EVI, human population density, and annual mean temperature rasterstack by first resampling landcover and EVI with the *resample* function to the resolution of human population density, which is ~ 1 km. Specifically, we used the 'nearest neighbor' and 'bilinear' methods to resample covariates of landcover and EVI tohuman population density, respectively.

Statistical models

Occupancy model

Using the presence/non-detection data from eBird, we fitted a hierarchical single species occupancy model that separately accounted for ecological and detection processes (Dorazio et al. 2010) affecting wild turkey observations across Florida. Specifically, we used the *spOccupancy* package (Doser et al. 2022) to test the effects of forest, shrub, human population density, crops, vegetation greenness (EVI), urban, grassland, water, temperature, and elevation-modulated wetland covariates. To prepare the data, we used the *format_unkmarked_occu* function in the *auk* package (Strimas-Mackey et al. 2025). In this function, site was defined as the geographic coordinates of the eBird checklist, site covariates were number of observations, geographic location, presence of forest, shrub, urban, crops, grassland, and water at site, EVI, population density, annual mean temperature, and elevation in wetlands. Observation covariates included date (day of year, linear and quadratic terms), time at which observation started, duration of survey in minutes, distance traveled during survey, and number of observers. All covariates were centered and scaled using their mean and standard deviation before fitting the model. For model fitting, we used the *spPGOcc* function in the *spOccupancy* package (Doser et al. 2022) to run three chains with 500 and 50 number of batches and batch length, respectively while specifying 5000 samples as burn-in. We set the thinning rate at 10 resulting in a total of 6000 posterior samples. To assess model convergence, we used a combination of visualizing the trace plots and Gelman-Rubin diagnostics, with $\text{Rhat} < 1.1$, indicating model convergence (Gelman and Rubin 1992). Using the posterior samples, we computed posterior mean and the 95% credible intervals for the different covariates that influenced occupancy.

Integrated model to estimate relative abundance

We modeled wild turkey relative abundance across Florida during the brooding season between 2020 and 2023. Unlike absolute abundance, relative abundance may be estimated from relatively less structured data sets such as citizen data and provide insight into population distribution (Callaghan et al. 2024). We combined all three data sources (eBird, FWC, and iNaturalist) using the data integration protocols within the *PointedSDMs* package (Mostert and O'Hara 2023). The integrated model consisted of three likelihoods for our three data sets: eBird, FWC, and iNaturalist, providing presence-non-detection, counts, and presence-only information, respectively. We chose to model eBird as presence-non-detection to account for sampling and spatial bias. This model framework then uses joint likelihood to estimate the ecological parameters using all data; while allowing for the incorporation of dataset-specific variables that describe their contrasting observation/sampling processes (Isaac et al. 2020).

To jointly model the ecological factors, the presence-non-detection (Eq. 1), count (Eq. 2), and presence (Eq. 3) sub-models shared the same covariates described above. Moreover, the three models shared a common spatial term, ξ_{shared}, that described potential autocorrelation between observations, but each model had a distinct intercept.

Specifically, this means that we specified the following linear predictors:

$$\text{eBird: } \mathrm{Y}_{eBird} \sim \text{ Binomial}\left(p_i\right)$$

$$c\log \cdot \log(p_i) = \alpha_{eBird} + \beta_{1,eBird}x_1 \ldots \beta_{n,eBird}x_n + \xi_{shared}(s) \tag{1}$$

where, Y_{eBird} is the binary presence-non-detection response while ρ_i represent the probability of the presence of wild turkey at location i. The complementary log–log link function links the probability of presence to the covariates described above ($x_1 – x_n$) and their coefficients $(\beta_{1,eBird} - \beta_{n,eBird})$

$$\begin{aligned} &FWC: \cdot Y_{FWC} \sim Poisson\left(\exp^{\eta FWC(S)}\right)\eta_{FWC}(S) \\ &=_{FWC} + \beta_{1,FWC}x_1 \ldots \beta_{n,FWC}x_n + \xi_{shared}(s) + \xi_{bias[FWC]}(s) \end{aligned} \tag{2}$$

$$\begin{aligned} &\text{iNaturalist: } \cdot Y_{iNat} \sim Poisson\left(\omega(s) \cdot \exp^{\eta_{iNat}(s)}\right)\eta(s) \\ &=_{iNat} + \beta_{1,iNat}x_1 \ldots \beta_{n,iNat}x_n + \xi_{shared}(s) + \xi_{bias[iNat]}(s) \end{aligned} \tag{3}$$

Where Y are the counts and presence points of each respective dataset, and η is the intensity of the underying point pattern of species presences, and ω(s) is the thinning parameter of this point pattern for iNaturalist data to reflect imperfect detection, and ξ_{bias} describes an additional spatial term to describe spatial bias in recording effort affecting the presence-only and count data.

To represent the observational processes affecting each dataset, we included time at which observation started, duration of survey in minutes, distance traveled during survey, number of observers, and date for the presence-non-detection dataset (eBird), while specifying only date for presence-only (iNaturalist), and count data (FWC) as detection covariates by specifying 'pointCovariates' withing the *startISDM* function. To account for the spatial bias of recorder affecting the presence-only (iNaturalist) and count dataset (FWC), we followed the recommendation of Simmonds et al. (2020) and used the *addBias* function to create a second spatial field.

We specified penalized complexity priors on the range and variance. Specifically, we set the prior such that there is a 95% probability that the spatial range (i.e., the distance at which spatial autocorrelation becomes negligible) is greater than 5 km. This reflects the assumption that spatial dependence in wild turkey observations is unlikely to occur at very fine spatial scales. For the variance of the spatial field, we set a prior with 95% probability that the standard deviation lies between 0 and 5, thereby limiting extreme spatial heterogeneity unless strongly supported by the data. We tested different combinations of the four prior specifications and found that the analysis was not sensitive to these decisions (Fig. S2). To map relative abundance (or rather, intensity of the point pattern), we used the *predict* function from the *PointedSDMs* package (Mostert and O'Hara 2023) on 10000 samples. This function draws on the integrated model to generate predictions of relative abundance for each grid cell. We plotted the data using the *st_as_stars* function from the *stars* package (Pebesma and Bivand 2023) to create Fig. 3B and set up the data for the comparison of relative abundance inside and outside the FLWC.

To assess model fit while accounting for spatial structure in the data, we used the *blockedCV* function to implement spatial block cross-validation. This analysis resulted in a cross-validated deviance score for each spatial block, which was used to evaluate the model's predictive performance while accounting for spatial autocorrelation. We divided the study area into spatial blocks using a 10 × 10 grid (rows × columns) and specified 5 folds ($k = 5$) for cross-validation using the *spatialBlock* function from the *PointedSDMs* package (Mostert and O'Hara 2023). To assess the influence of each dataset on the integrated model, we conducted a dataset exclusion analysis using the *datasetOut* function from the *PointedSDMs* package (Mostert and O'Hara 2023), refitting the integrated model while systematically leaving out one dataset at a time. This approach allowed us to evaluate the relative contribution of each dataset to model performance and parameter estimates.

Assessing variation in occupancy, relative abundance, and productivity inside and outside the FLWC

To compare wild turkey occupancy and relative abundance inside and outside the FLWC, we used the occupancy model and the integrated model to predict occupancy and relative abundance (at 95% credible intervals) of the species, respectively, across the whole of Florida at a resolution of 1 km^2. We then compared the mean predicted occupancy and relative abundance (and standard deviation) of pixels that were inside and outside the FLWC. We focused on comparing predicted occupancy and abundance rather than including FLWC as a covariate in the models themselves (Eqs. 1–3), because our interest was in assessing whether the FLWC protects areas with higher predicted abundances of wild turkey across the whole region. To do this, we fit a Gaussian generalized linear model to the data, where the predicted occupancy and relative abundance were treated as response variables and Corridor (inside vs. outside the FLWC) was the main predictor of interest. We evaluated model fit using the *r2* function in the *performance* package (Lüdecke et al. 2021) to obtain R^2.

To assess the effects of the FLWC on wild turkey productivity, we investigated variability in the number of poults and poults per hen inside compared to outside the FLWC using the demographic information from the FWC data set. Specifically, to assess the effect of the FLWC on the number of poults, we used the glmmTMB package (Brooks et al. 2017) to fit a zero-inflated Poisson generalized linear model. Corridor (inside vs. outside the FLWC) was included as the main predictor of interest. Year (2020–2023) was included as a fixed effect to account for interannual variation, as the model did not converge when Year was treated as a random effect due to the small number of levels. We also quantified turkey productivity by computing the poults-per-hen ratio (a general productivity index for the species) and using this ratio as a response variable, fitted a generalized mixed-effect model with a log-link gamma distribution treating year and corridor like the poult abundance model described above. To determine model fit, we used the *r2* function in the *performance* package (Lüdecke et al. 2021) to obtain adjusted R^2.

Results

Effects of land cover, temperature and human population on occupancy and relative abundance

Wild turkey occupancy was positively associated with forest (mean = 0.48, CRI = 0.003–1.62), grassland (mean = 1.86, CRI = 0.36–4.24), shrub (mean = 1.49, CRI = 0.024–3.68), and increased with elevation gain in wetland habitat (mean = 0.51, CRI = 0.13–1.00). On the other hand, occupancy was negatively associated with human population (mean = −1.08, CRI = −1.64–−0.57), temperature (mean = −0.50, CRI = −0.85–−0.17), and urban (mean = −0.48, CRI = −0.85–−0.12). Crops (mean = −0.13, CRI = −0.35–0.1), EVI (mean = − 0.31, CRI = − 0.66–0.04), and water (mean = −0.05, CRI = −0.25–0.17) did not have a significant positive or negative trend with

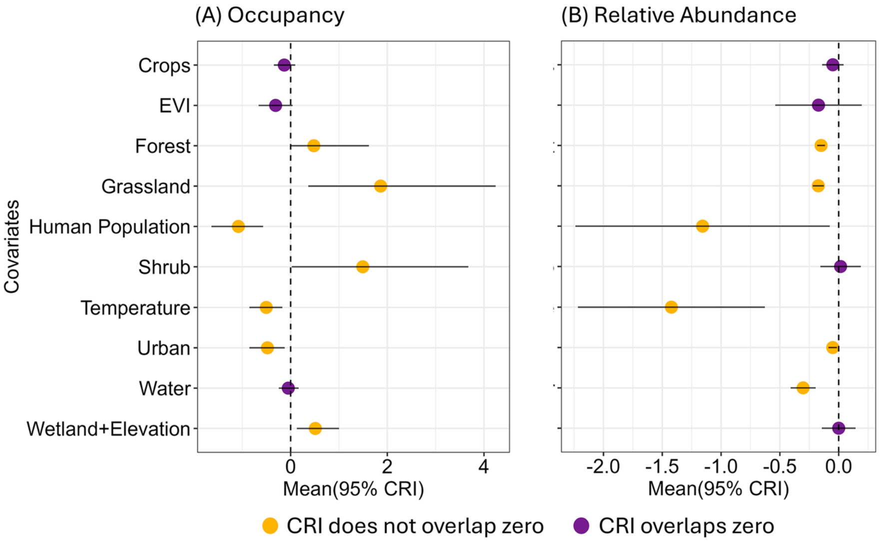

Fig. 2 The effects of the various covariates on wild turkey occupancy **A** and relative abundance **B** across Florida. Points representing posterior means and error bars reflect the 95% credible intervals. Wetlands account for elevation, so this reflects the relationship between wild turkey occupancy and relative abundance across the elevation gradient within this habitat. Purple points represent variables which the CRI overlaps zero, whereas yellow points represent variables for which the CRI does not overlap zero

wild turkey occupancy (Fig. 2A). Regarding effects on variation in wild turkey relative abundance, crops (mean = − 0.05, CRI = −0.14–0.04), EVI (mean = − 0.17, CRI = −0.54–0.20), shrub cover (mean = 0.02, CRI = −0.16 – 0.19), and elevation in wetland (mean = 0.00002, CRI = −0.14 – 0.14) did not have a significant negative or positive trend with wild turkey relative abundance (Fig. 2B). Conversely, temperature (mean = −1.42, CRI = −2.22 – −0.63), forest (mean = −0.15, CRI = −0.18–− 0.12), grassland (mean = −0.17, CRI = −0.22 – −0.13), human population (mean = −1.16, CRI = −2.24 – −0.08), urban (mean = −0.05, CRI = −0.09 – -0.01), and water (mean = −0.30, CRI = −0.41 – −0.20) drove negative associations (Fig. 2B).

General variability in occupancy and relative abundance across Florida

Predicted wild turkey occupancy was marked by distinct patterns (Fig. 3A), tending to be higher in the northern part of the state, where Eastern wild turkey's occur, and lower in the southern part of the state across the Osceola range. Moreover, the species' occupancy was invariably low across urban areas and areas experiencing agricultural intensification. Occupancy patterns varied substantially across southwestern Florida. Likewise, estimated relative abundance varied across Florida with low populations predicted in southern Florida, around urban and agricultural areas (Fig. 3B).

Spatial block cross-validation revealed that DIC values ranged from 35,834 to 42,063 across the five spatial folds, with a mean DIC of 39,900, indicating variation in model performance depending on spatial partitioning. The leave-one-dataset-out cross-validation analysis identified the FWC dataset as the most influential contributor to model performance (CV = 85,362). The eBird dataset also provided valuable information (CV = 2,795), while the iNaturalist dataset had relatively little impact on the model (CV = 191).

Variation in occupancy, relative abundance, and productivity inside and outside the wildlife corridor

Predicted mean wild turkey occupancy was higher inside (mean = 0.64, SD = 0.31) compared to outside (mean = 0.44, SD = 0.28) the FLWC ($\beta=0.194$, SE = 0.001, $p<0.005$, $R^2=0.168$) (Fig. 4A; Table S2). This relationship held true across the Osceola subspecies ($\beta=0.192$, SE = 0.001, $p<0.005$, $R^2=0.163$) and the Eastern wild turkey subspecies ($\beta=0.131$, SE = 0.001, $p<0.005$, $R^2=0.160$) (Fig. 4E). Relative abundance was greater inside (mean = 0.41, SD = 0.41) compared to outside (mean = 0.40, SD = 0.37) the FLWC ($\beta=0.015$, SE = 0.004, $p<0.005$, $R^2=0.002$) (Fig. 4B). The effect size of this relationship was positive in the Osceola subspecies ($\beta=0.039$, SE = 0.006, $p<0.005$, $R^2=0.012$) compared with negative in the Eastern wild turkey subspecies ($\beta=-0.023$, SE = 0.004,

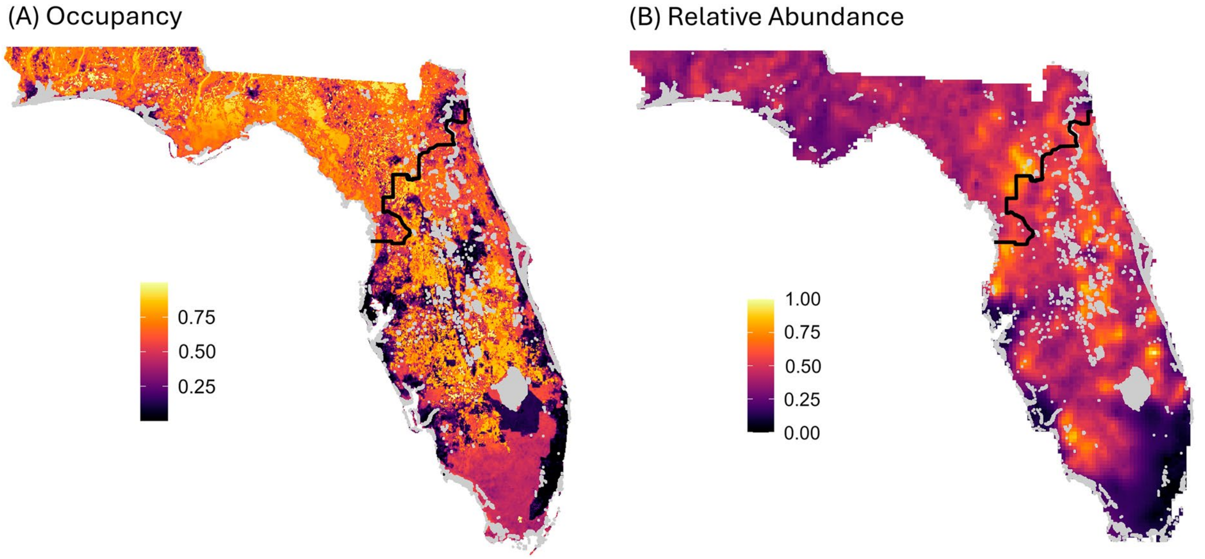

Fig. 3 Variability in wild turkey occupancy **A** and relative abundance **B** across Florida between 2020 and 2023. The black line represents the regional separation of Eastern wild turkey (north/northwest of line) and Osceola wild turkey (south of line). Warm colors indicate areas with high occupancy or population abundance while grey patches are open water bodies. Maps of uncertainty for each model can be found in Fig. S3

$p<0.005$, $R^2=0.012$) (Fig. 4F). Although these relationships were statistically significant, the corridor explained little of the variation in relative abundance across comparisons. When we compared the upper quartile variation in predicted wild turkey occupancy and relative abundance, we found that predicted occupancy was similar inside and outside of the FLWC, while relative abundance was somewhat higher inside compared to outside the corridor (Fig. S4).

There was no difference in the number of poults inside (mean = 3.09, SD = 5.90) versus outside (mean = 3.05, SD = 5.04) the FLWC (β = -0.030, SE = 0.016, $p=0.061$, adj $R^2=0.01$) (Fig. 4C). Similarly, the number of poults per hen did not vary inside (mean = 2.03, SD = 2.66) compared to outside (mean = 1.95, SD = 2.61) the FLWC (β = -0.017, SE = 0.025, $p=0.491$, adj $R^2=0.011$) (Fig. 4D).

Discussion

Our results suggest that the FLWC had a positive effect on wild turkey occurrence and abundance. Given that human development was the strongest negative predictor of wild turkey relative abundance and occupancy, and the positive effect size was greatest in the most developed region of the state across the Osceola subspecies range, the FLWC may be particularly important in the long-term conservation of wild turkeys in Florida and has been serving its primary purpose of halting development. Productivity metrics were not associated with the FLWC. The higher predicted occupancy and abundance within the FLWC likely reflect the combined effects of greater habitat availability or quality, reduced human pressure, and possibly improved movement or survival of adults within connected landscapes. For example, there could be differences in poult and adult female survival which are moderated by edge effects leading to greater exposure to predators within and outside the FLWC. Adult female survival is the most important vital rate influencing wild turkey population growth (Londe et al. 2023), and adult female survival has recently declined across the range of wild turkeys (Lashley et al. 2025). Importantly, we did not measure these mechanistic explanations and suggest future work should incorporate movement and survival data to further refine a mechanistic understanding of how the FLWC supports higher relative abundance and occupancy of wild turkeys.

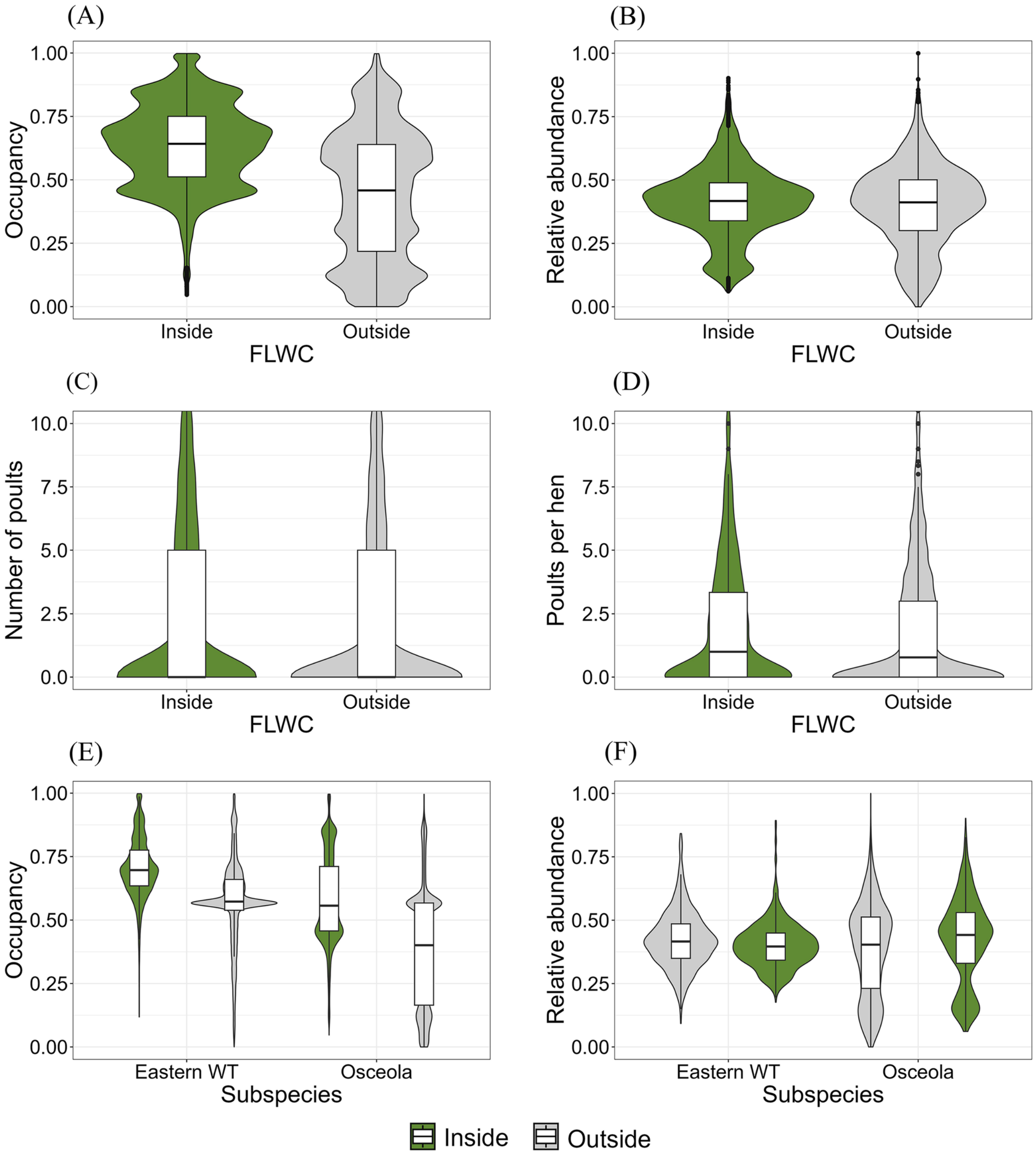

Fig. 4 Variation in occupancy **A** and relative abundance **B**, the number of wild turkey poults **C** and poults per hen **D** inside and outside the Florida Wildlife Corridor (FLWC) during the brooding seasons between 2020 and 2023. Panels, **E** and **F** shows variation in occupancy and relative abundance, respectively, of the Eastern wild turkey (Eastern WT) and Osceola Wild Turkey (Osceola) subspecies. In the boxplots, the horizontal line inside each box shows the median and the box spans from the 25th to the 75th percentile. For productivity measures (C and D), data were filtered to remove outliers above the 99th percentile to improve visualization. To see the full plots without outliers removed, Fig. S4

Relationships between land cover, temperature, and human population on wild turkey occupancy and relative abundance

Both predicted wild turkey occupancy and relative abundance were low across the southern part of Florida and within urban areas or areas experiencing agricultural intensification (e.g., near Lake Okeechobee). We found some mismatch between occupancy and relative abundance across Florida, contradicting the expectation that areas highly occupied by a species also tend to support greater number of individuals (Gaston et al. 2000). Both urbanization and the human population negatively impacted the species' occupancy and relative abundance. Urbanization may pose a direct threat to wildlife by increasing animal-vehicle collision (Conover et al. 1995; Kays et al. 2017; Wightman et al. 2023) or indirectly through a suite of other disturbances (Venter et al. 2016), resulting in widespread landscape avoidance (Ciuti et al. 2012) and/or altered animal distribution.

Similar to studies that have predicted associations between vegetation heterogeneity and wild turkey broods (Chamberlain et al. 2020; Nelson et al. 2023), our results showed a positive link of occupancy with forest, shrub, and grass cover which supports this premise. Co-occurring grasslands, shrubs, and forests represent heterogeneous landscapes associated with high biodiversity (Tews et al. 2004). While trees and shrubs may provide cover and suitable roosting sites (Chamberlain et al. 2020), relatively open landscapes such as grasslands and early successional vegetation provide suitable foraging ground for broods by facilitating ease of poult movement while providing concealment (Little et al. 2016). Relative abundance was negatively associated with forests and grasslands and showed no relationship with shrublands, indicating that different vegetation types distinctly shape turkey distribution in the southeastern United States. Furthermore, closed canopies may present challenges associated with lack of suitable vegetation for nesting and brood-rearing.

More generally, other environmental covariates (e.g., water, grassland) differed in both the strength and direction of their effects between occupancy and relative abundance models. This difference between occupancy and relative abundance likely reflects how these two metrics respond to different ecological processes or scales. Occupancy models capture the probability of presence (i.e., whether habitat is suitable for wild turkeys to occur) while relative abundance captures how many individuals are likely to be present where turkeys do occur. Grasslands and forests, for example, were positively associated with occupancy but negatively associated with relative abundance. These discrepancies may arise from fine-scale habitat differences. For example, both forest and grassland cover were associated with higher occupancy but lower relative abundance of wild turkeys. Although this may seem contradictory, it is likely due to variation in habitat quality within these land cover types. For example, grasslands can range from sod-forming grasses to native longleaf pine (*Pinus palustris*) savannas, and forested areas may greatly differ in structure and management (e.g., prescribed fire). These differences illustrate the importance of considering both occupancy and relative abundance to fully understand how an organism responds to the landscape.

Although we found a slightly negative relationship with croplands, it is important to note that our cropland covariate included a variety of farming practices, likely with differing impacts on wild turkey occupancy. For example, empirically, we saw that high agricultural intensification practices, such as sugarcane farming, drove conspicuous negative effects across South Florida. Agricultural landscapes are predicted to enhance wild turkey foraging benefits (Pollentier et al. 2017) and farms that maintain native vegetation cover may contribute to habitat availability, which was observed in parts of northern Florida. Agricultural management may alter predator dynamics and shape predator communities (Muhly et al. 2011). Furthermore, although there was no significant positive association of crops with predicted wild turkey relative abundance, highly productive landscapes such as agricultural mosaics can attract high animal densities (Lewis et al. 2015) to exploit ephemeral resources. Regarding climate-related impacts, the negative and positive associations of occupancy and relative abundance with mean annual temperature, respectively, reflect the complex nature of potential climate impacts on wild turkey during the breeding season in the southeastern United States (Boone et al. 2024, 2023). Temperature variation may drive fine-scale habitat selection while simultaneously impacting broadscale population dynamics. On the other hand, although flooding can be detrimental for ground-nesting avian species (Fisher et al. 2015), perhaps ephemeral wetlands such as those occurring at higher elevations contributes to wild turkey productivity.

Relationships between occupancy, relative abundance, and productivity and the FLWC

Low predicted wild turkey occupancy and relative abundance outside the FLWC are unsurprising given the high human population and presence of other disturbances such as urbanization and agricultural intensification (Fig. 1), including the historical high rate of general land use intensification outside the FLWC (Daskin et al. 2024) that influences habitat loss. Our results suggest that the FLWC may form important core areas that correlate with wild turkey populations similar to what has been demonstrated in sage-grouse-landscape associations (Burkhalter et al. 2018). This may be especially true if areas outside the FLWC experience increased development, agricultural intensification, and population density, as the corridor could then provide an even greater benefit to wild turkey occupancy (see supplementary analysis described in Fig. S6). However, the effect size of the FLWC on predicted occupancy and population abundance was likely conservative because the corridor also encompasses unsuitable turkey habitat such as the Everglades (a wetland) region. Further, although the differences in predicted occupancy and relative abundance inside versus outside the FLWC were statistically significant, the amount of variation explained by the corridor was small ($R^2 = 0.015$). This suggests that while the pattern is consistent across analyses, the biological effect is modest in magnitude and the observed differences are likely driven by indirect effects, as mentioned above.

We found that the Osceola subspecies is expected to benefit from the FLWC as it had greater predicted occupancy and relative abundance inside the FLWC. In contrast, the Eastern subspecies is only expected to benefit in terms of greater predicted occupancy but not necessarily relative abundance. Unlike the Eastern wild turkey, the Osceola wild turkey is endemic to Florida and therefore loss in natural vegetation and increase in human pressure would have significant impacts for the subspecies. Particularly, most development and increase in human population is occurring across the Osceola range and therefore creation and maintenance of turkey habitat within the FLWC and surrounding landscapes is crucial for conservation of this endemic subspecies. This relationship highlights a couple of important findings to inform strategic efforts to plan wildlife corridors. First, urbanization is a primary proximate threat and second, the effectiveness of wildlife corridors increases with increasing urbanization. Productivity may not be related to the FLWC because there is no substantial difference in turkey nesting and brood-rearing habitat quality within or outside the corridor at large scales. Variability in wild turkey productivity may be a functioning at too fine of a spatial scale for those differences to be evident in the FLWC. Fundamentally, given that our study does not support productivity as the mechanism underlying the greater predicted occupancy and relative abundance within the FLWC, we speculate that adult survival represents an alternate driver of these patterns as increased connectivity can enhance access to resources. However, further research is warranted to confirm these patterns.

Importantly, the FLWC was only formally established in 2021 and therefore our analyses do not evaluate changes before and after its creation. Instead, interpretation of the above patterns should be in the currently observed relationships between predicted wild turkey occupancy, relative abundance, and productivity inside versus outside the areas encompassed by the FLWC. These patterns therefore reflect how landscapes currently designated within the corridor differ from surrounding regions, rather than direct mechanistic effects of the FLWC. The corridor designation did not itself generate new habitat or immediate ecological changes but consolidated and prioritized lands that were already functioning as wildlife habitat. Therefore, a “before-and-after” comparison is less meaningful than evaluating current differences between areas inside and outside the corridor. Our findings highlight the conservation value of these areas and provide an important baseline for future evaluations of how ongoing protection and management within the FLWC influence wildlife populations over time.

Challenges and opportunities to expand on this study

While we frame our results within the context of the FLWC, we acknowledge that the FLWC encompasses more than narrow corridors. It is a mosaic of public and private lands with varying degrees of connectivity, and as such, our results reflect broader landscape-scale conservation value rather than the specific functional role of narrow corridors (e.g., Gilbert-Norton et al. 2010; Resasco 2019). Importantly, our study suggests that wildlife corridors across the southeast may be critical for wild turkey resilience by minimizing population impacts. The use of citizen science data in ecological modeling is increasing and filling gaps complementing many structured surveys (Hadj-Hammou et al. 2017) while contributing to generation of strong species distribution inferences (Strebel et al. 2022) and thus conservation policies (Wyeth et al. 2019). Additionally, while some data quality checks exist among big data platforms such as eBird and iNaturalist including large-scale camera trap projects (e.g., Cove et al. 2021), agencies should continue to collect high-quality data in structured formats. Such structured data are complementary to citizen science data, allowing for integrated models, such as the one fitted here, to be continually fit and updated or validated (Morera-Pujol et al. 2023). Our study contributes to the growing field of integrated modelling, providing a use-case scenario for how these models can and should be applied in the future. For example, by strategically designing local-scale surveys that complement broad-scale citizen science efforts to capture fine-scale habitat associations, especially during critical periods of a species such as brooding, then more fine-scale patterns of organismal responses can be disentangled.

Conclusion

We demonstrated the importance of the FLWC to wild turkeys, particularly the endemic Osceola subspecies, similar to other species (e.g., Dixon et al. 2006; Letro et al. 2022; Leskova et al. 2022), and that the FLWC Act has the potential to protect habitat that is suitable to wild turkeys. Given that about half of the wildlife corridor currently comprises opportunity areas (that are vulnerable to development), maintaining the corridor's conservation value will require prioritizing strategic protections in these landscapes. This is especially critical in the southeastern U.S., where natural lands are less connected (McGuire et al. 2016) and underrepresented in the protected area network. Because the influence of the FLWC varied between the species' distribution (occupancy and relative abundance) and productivity, studies evaluating the role of wildlife corridors should consider species productivity whenever possible. More work is needed to quantify and evaluate the benefits of the FLWC, and other large-scale habitat connectivity networks, for multi-species approaches.

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Data availability Data and code to reproduce these analyses are available here: https://doi.org/10.5281/zenodo.17574714.

Declarations

Conflict of interest Authors declare no competing interests.

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