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Does Urbanization Surrounding Stopping Sites Affect Migratory Behavior in American Woodcock (Scolopax minor)?

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DOES URBANIZATION SURROUNDING STOPPING SITES AFFECT MIGRATORY BEHAVIOR IN AMERICAN WOODCOCK (*SCOLOPAX MINOR*)?

by

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ABSTRACT

Urban landscapes may influence bird species in complex ways, with some species exploiting urban environments, others adapting to them, and others avoiding them. Migratory birds encounter urbanization not just during breeding and overwintering, but also at stopping sites during migration. Migration routes of American Woodcock (*Scolopax minor*), a bird species experiencing long term population declines, follow the east coast of the United States, including the major urbanized areas of the eastern seaboard. I explored the effects of urbanization around stopping sites on Woodcock migratory behavior using the percentage of impervious surfaces within a buffer surrounding the site as a measure of urbanization. I used four variables to quantify stopping behavior: stopover duration, average movement distance within stopover, stopping event type (stop or stopover), and subsequent migratory step length. I predicted that greater levels of urbanization would result in less favorable stopping sites, which I hypothesized would be associated with shorter stopping events, a greater likelihood of stops as opposed to stopovers, longer movements within stopovers and a shorter subsequent migratory step length. I used a tiered AICc model selection approach with generalized linear models, while accounting for the potential confounding effects of demographic, spatial, and temporal variables on Woodcock behavior. I found little evidence that impervious surface cover affected Woodcock migratory stopping behavior, which could indicate that urbanization in their migratory range is not a major concern for the species. However, I also noted a low frequency of stopping sites in very urbanized areas and some non-linear patterns in the data, which may suggest a potential threshold effect that could be investigated by further study.

ACKNOWLEDGEMENTS

I could not have completed this project without the help of so many kind people. My advisor, Erik Blomberg, provided so much help, support, and guidance. The data I used for my thesis was prepared by Sarah Clements, who gave her knowledge and time to help me get started on my thesis. Liam Berigan was generous and indispensable in helping me figure out how to solve issues with my data and figure out the software I used for my thesis. My work is built off the previous work of the Eastern Woodcock Migration Research Cooperative (www.woodcockmigration.org). Many people on this project contributed to collecting the field data I used and generating knowledge that helped inform my approach. Thank you all.

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INTRODUCTION

As of the 2018 revision to United Nations World Urbanization Prospects report, the proportion of the world's population living in urban areas was 55%, and this number was even greater in North America at 82% (United Nations, Department of Economic and Social Affairs, Population Division, 2019). Urbanization may affect wildlife health, abundance, and diversity. For example, Murray et al. (2019) found in a meta-analysis that greater levels of urbanization were associated with greater close-contact-transmitted parasitism and higher toxicant loading in wildlife but did not find a significant effect of urbanization on body condition or stress levels. The number of detected vertebrate animals and species has been found to decline between before and after surveys at developed sites, including significant decreases in bird abundance and the number of bird species (Smallwood and Smallwood 2023). Medium to large mammal occupancy in cities and its response to urbanization gradients is influenced by variation between cities of landscape factors like housing density and amount of greenspace (Fidino et al. 2020). On a larger spatial scale, greater urbanization may be accompanied by increasing wildlife populations as land uses shift and human impacts become more concentrated: for example, as rural populations in an area decrease and less land is devoted to agriculture (Izquierdo et al. 2018).

Urbanization may impact bird species in often complex ways. Urban environments provide a unique set of challenges for birds, including chemical, noise, and light pollution, habitat fragmentation, and disturbance by humans (Isaksson 2018 and references therein). They may also have some potential benefits, which may include the presence of novel (but often low quality) food sources, abundance of prey (for predatory birds), new nesting habitats, and warmer climates caused by urban heat islands (Isaksson 2018 and references therein). However, bird species diversity is lower in cities than predicted based on range maps, and land cover has been found to be a predictor of species density, with percentage of urban land cover negatively correlated with bird species diversity (Aronson et al. 2014). A study of Acadian Flycatcher (*Empidonax virescens*) found that adult and nest survival were not affected by urbanization, while reproductive output was negatively associated with urbanization, with pairs in more urbanized environments initiating the breeding season later and urban nesting sites showing a higher rate of turnover (Rodewald and Shustack 2007). Not all bird species respond equally to urbanization, and the mechanisms behind success in urban environments are often complex and species-dependent (Isaksson 2018 and references therein).

Migratory birds may encounter urbanization and land cover changes not only during breeding and winter, but also during migration. Stopover is an important aspect of migration, defined by Schmaljohann et al. (2022) as “an interruption of migratory endurance flight to minimize immediate and/or delayed fitness costs". The individual functions of stopover that promote fitness may include energy store replenishment, physiological recovery, and avoidance of adverse environmental conditions (Schmaljohann et al. 2022). Anthropogenic changes to land cover may alter the functionality of stopover habitat, although some studies have found that urban sites can fulfill birds’ requirements for stopover. Stopover in New York City parks, for example, may provide similar refueling opportunities as nearby non-urban sites (Seewagon et al. 2011). Hereafter, I use the term “stopping event” to refer to all instances where

Woodcock paused migratory flight, while I use the term “stopover” for longer stopping events of >1 day and “stop” for shorter stopping events lasting only a single day. Stops are shorter routine pauses in migration and are important to distinguish from stopovers, where the bird has chosen to interrupt migration for longer to allow for a greater period of resting and refueling.

The American Woodcock (*Scolopax minor*) is a migratory bird with a range from southern Canada through the eastern and central US, extending as far south as northern Florida, with wintering grounds in Maryland and southern New Jersey and farther south. (Seamans and Rau 2019). Population monitoring has shown long term trends of population decreases between 1968 and 2017 (Seamans and Rau 2019). At Cape May, New Jersey, migrating woodcock were more likely to select stopover sites with shrubland and wetland forest land cover, selected against urban land cover types, and differed in their habitat selection from overwintering woodcock (Allen et al. 2020). Stopover site selection in migrating Woodcock may be related to resource availability and proximity to roosting sites (Allen et al. 2020). One well documented link between urbanization and adverse effects on Woodcock is collisions with buildings, which may be a major source of mortality for migrating Woodcock, particularly in the spring and during inclement weather conditions (Loss et al. 2020). The decline in Woodcock populations has been attributed largely to habitat loss (Kelley et al. 2008), and since urbanized areas represent highly modified habitat, investigating the response of Woodcock to urbanization during migration is relevant to understanding their long-term decline. To my knowledge, however, no previously published work has specifically examined the impact of urbanization on Woodcock migratory behavior.

My goal was to determine the relationship between urbanization surrounding migratory stopping sites and migratory behaviors in American Woodcock. My specific objectives were to determine the relationship between urbanization and 1) the duration of migratory stopping events and 2) movements during and immediately following the migratory stopping event. I hypothesized that greater levels of urbanization would result in shorter migratory stopping events, greater average movement distance within stopovers, and shorter migratory step distances.

METHODS

Data Collection and Processing

I used GPS tracking data collected by the Eastern Woodcock Migration Research Cooperative (www.woodcockmigration.org) and summarized by Clements et al. (2024). Woodcock were captured in 14 US states and 3 Canadian provinces in the years 2017-2022. Captured birds were aged and sexed, classified as “young” (birds making their first fall or spring migration) or “adult” (all birds after their first migration), and fitted with Lotek fixed-battery PinPoint 75, PinPoint 120, or PinPoint 150 GPS Argos transmitters (Clements et al. 2024). The transmitters collected one location with an accuracy of 20 m approximately every 1-2 days during the first migration following capture, and approximately every 5-7 days thereafter. All GPS locations were considered to be part of a migratory stop or stopover because the birds were assumed to migrate nocturnally and stop every day (Clements et al. 2024). I used migration metrics calculated by Clements et al., with relevant additional steps described below. Data points were classified as fall or spring migration based on date (August 1st to December 31st for fall migration, and January 5th to June 15th for spring migration), and stopping events were classified as stopovers when another datapoint occurred within 16 km or stops when another datapoint did not occur within 16 km. The 16 km threshold was used to separate migratory flights from shorter non-migratory movements following Blomberg et al. (2023), because their analysis revealed a bimodal distribution separating movement distances above and below 16 km. Stopover duration and the average distance of the movements made within each stopover were also calculated prior to my use of the data.

Quantification of Migratory Behavior

I investigated my research questions through four variables: whether a stopping event was a "stop" or a "stopover", the duration of the stopping events that had been classified as stopovers, the average distance of movements within the stopping event (applicable only to stopovers), and migratory step distance (the length, in kilometers, of the next leg of migration from the current to the next stopping event). Stopover duration was the estimated amount of time, in hours, that a Woodcock spent at a particular stopover, excluding stops, which only contained one recorded point and were by definition <1 day in length. I accounted for the <1 day stops with my inclusion of the stop type variable, which was a binary measure indicating whether each migratory stopping event was a stop or a stopover. I included these measures of the amount of time spent at each site because I predicted that Woodcock would spend a shorter amount of time in urbanized areas with sub-optimal conditions. I included the average distance, in km, of the movements made by Woodcock within stopovers because I predicted that Woodcock would travel farther distances when encountering more disturbance during stopovers, or because their immediate area didn't provide adequate resources. Migratory step distance was the distance, in km, that Woodcock flew between the current stopping event and the next stopping event. I included this variable to assess whether migratory stopping events in developed areas provided adequate resting and refueling opportunities; I predicted that Woodcock would be able to fly longer distances if they'd adequately rested and refueled at the previous stopping event. I calculated migratory step distance as the distance between a stopping event and the next stopping from the same bird using the function "distVincentyEllipsoid()" in the package 'geosphere' (Hijmans 2022) in program R (R core team 2023). Because stopping events are designed to maximize short-term and long-term fitness (Schmaljohann et al. 2022), Woodcock migratory behavior surrounding stopping events is important in balancing continuing migration vs the refueling and recovery aspects of stopping. The variables I use to quantify migratory behavior demonstrate aspects of this balance: the amount of time spent migrating vs stopping, the distance traveled between periods of refueling and recovery, and the balance between accessing potentially better resources vs expending energy to travel longer distances within stopping events.

Quantification of Urbanization

There are many different ways to measure urbanization (Moll et al. 2019). Different metrics of urbanization may have their own pros and cons but are generally attempting to measure the same underlying processes. I used the mean percent impervious surface cover over a set distance from stopping event center as a proxy for urbanization. This method is classified as a gray structural type, which is a common type of urbanization metric used in wildlife studies, likely in part because structural metrics can be used as a proxy to represent other aspects of urbanization that correlate with them (Moll et al. 2019). I chose this metric because its simplicity and availability made it practical for the scope of this analysis, and because I was interested in a metric that would stand in for other aspects of urbanization. I chose a metric that quantified more general aspects of the land cover and habitat Woodcock would encounter during stopover, rather than focusing on a specific factor such as light pollution or food availability. I obtained impervious surface cover data via the National Land Cover Database 2021 Percent Developed Imperviousness layer (Dewitz 2023, downloaded from https://www.mrlc.gov/data/nlcd-2021-percent-developed-imperviousness-conus). This raster dataset contained percent urban imperviousness over the continental US with a resolution of 30m. Some of my geospatial data management was done in ArcGIS pro (Esri 2023).

Because the impervious surface raster was specific to the US, I removed any stopping event points that occurred in Canada from my data set. I decreased the resolution of the impervious surface raster to 90m because the original raster was too large for my data processing capacity. I based the location of each stopping event on the geographic center of all locations that were collected for that stopping event. I calculated the percentage of impervious surface cover within two radii of each stopover location, 1.859 km and 3.900 km, by using the "st_buffer" function in the 'sf' package (Pebesma and Bivand 2023, Pebesma 2018) in program R (R core team 2023) to create a buffer of each radius around the migratory stop centroid, and functions within the terra R package (Hijmans 2023) to calculate the mean percent impervious surface cover within each radius (Fig. 1). These values were chosen because 90% and 95%, respectively, of within-stop movement lengths were under those distances.

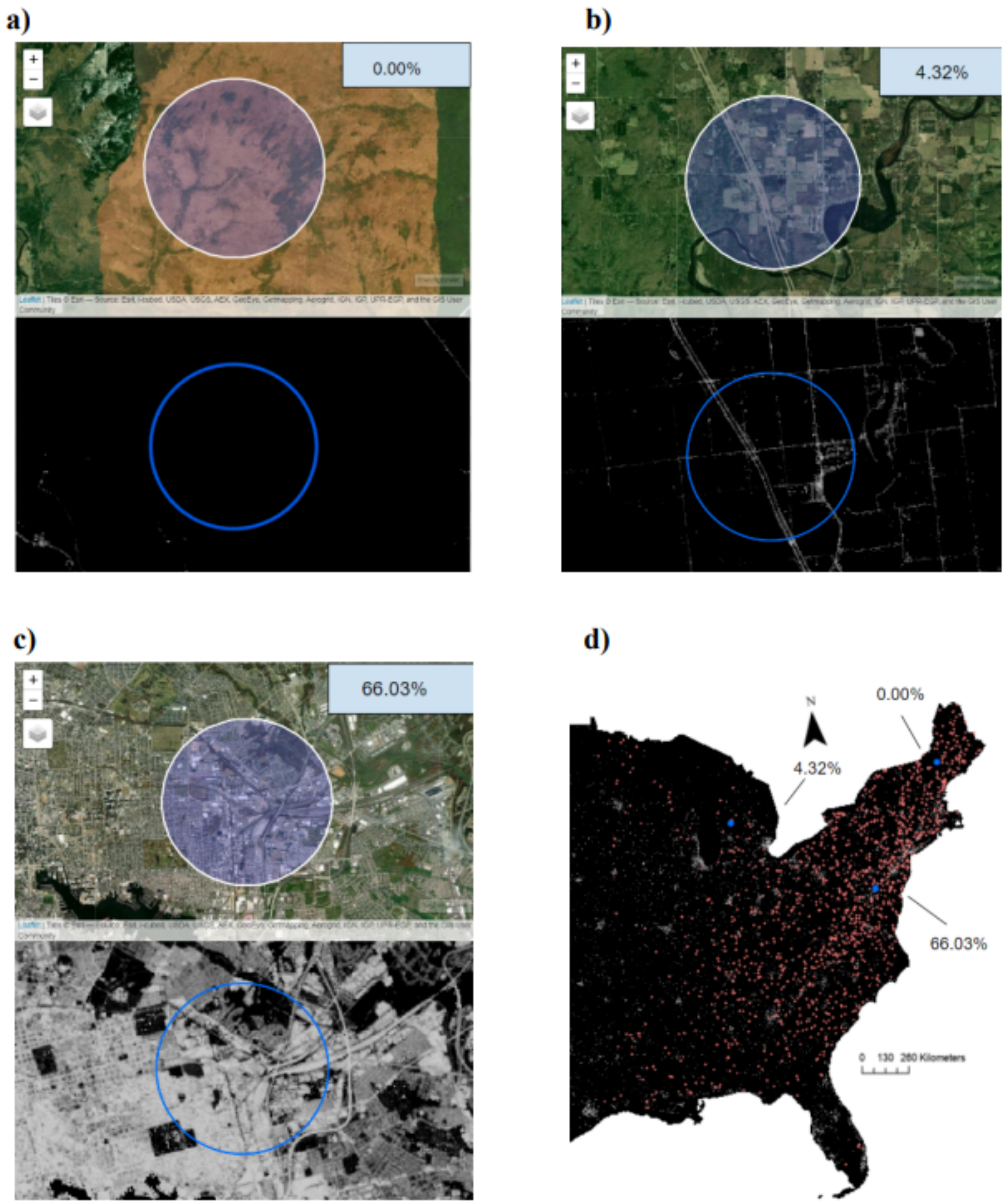

Figure 1. Migratory stop locations of GPS-tagged American Woodcock migrating through the eastern United States between 2017 and 2022. Blue and white circles show a 1.859 km radius from migratory stop center. Panels a, b, and c show the migratory stop over aerial imagery (top) and a raster layer displaying impervious surface cover (bottom), with lighter colors representing higher impervious surface cover. Panel a shows the point with the smallest amount of impervious surface cover within 1.859 km of stopover center (0.00%), Panel b shows the point with the percent impervious surface cover within 1.859 km of stopover center closest to the mean value for the dataset (4.32%), and Panel c

shows the point with the greatest amount of impervious surface cover within 1.859 km of stopover center (66.03%). Panel d shows the location of all recorded migratory stop points, in pink, with the larger blue points representing the locations shown in Panels a, b, and c. Panels a, b, and c were created using the mapview () function and imagery available in the mapview R package (Appelhans et al. 2023). Panel d was created in ArcGIS pro (Esri 2023). Impervious surface raster from the National Land Cover Database (Dewitz 2023), https://www.mrlc.gov/data?f%5B0%5D=category%3AUrban%20Imperviousness.

Confounding Variables

In addition to mean impervious surface cover, I included latitude, longitude, bird conservation region (BCR), Woodcock age, Woodcock sex, stopping event year, and stopping event date in my analysis as potential confounding variables and interactive effects with impervious surface cover. I included BCR to account for the effects of broadly defined habitat types relevant to avian communities on how Woodcock responded to urbanization. I used a polygon layer of BCRs from Bird Studies Canada and NABCI, 2014 (https://www.birdscanada.org/bird-science/nabci-bird-conservation-regions) to assign each data point the BCR where it was located. I combined BCRs 12 and 13, BCRs 22, 23, and 24, and BCRs 25, 26, 27, and 37 because a very small number of points in some BCRs prevented me from analyzing them separately. I analyzed date as a continuous numerical value representing the ordinal date relative to October 8th (the first day of the migration year, Fish et al. (2024). I assumed a-priori that season (fall or spring) would impact migratory behavior and performed the analysis separately for fall and spring data points.

Data Analysis

I ran all models as generalized linear models using the function “glm()” in program R (R core team 2023) and ran the models as Gaussian regressions for all variables except for stop type, which was run as a binary logistic regression. Initially, I attempted generalized linear mixed models, and included individual Woodcock as a random intercept in my models to account for repeated sampling, but the variance term for the random intercept failed to converge. Instead, I weighted each observation in the models by 1/the number of points for that individual Woodcock in order to reduce the impact of repeated sampling of individuals.

Prior to including variables as covariates in the same model, I used program R (R core team 2023) to test for correlations between them to ensure models did not contain multiple variables that were highly correlated. Because some of the variables (latitude, longitude, date, and mean percent impervious surface cover) were continuous, some (age and sex) were binary, and some (BCR and year) were categorical but not binary, I performed different statistical tests to assess the correlations between different variable pairs. I used either a chi-square test of independence or a Fisher's exact test to test for correlations between every pair of categorical variables, considering two variables correlated if the test produced a p-value of less than 0.05. I used a Pearson's correlation coefficient or a biserial correlation coefficient for each pair or two continuous or one non-binary categorical and one continuous variable, considering the two variables correlated if the correlation coefficient was greater than or equal to 0.7. For each pair of one categorical but non-binary variable and one continuous variable, I tested correlations with a linear regression, considering two variables correlated if there was a p-value of 0.05 less for at least one level and the adjusted R-squared value was 0.5 or greater. I tested correlations separately for the specific dataset used in each round of model selection after I performed any subsetting (removal of "stops" or last recorded points). I assumed that BCR was correlated with latitude and longitude.

I used a multi-tier model selection approach influenced by Fish et al. (2024). At each tier, I performed Akaike's Information Criterion corrected for small sample size (AICc), using the R package 'AICcmodavg' (Mazerolle 2023), to identify the most supported model. For each tier of analysis, the most supported model was carried forward and used as an additive effect in the next tier. The tiers I used were 1) individual variables (age, sex, age+sex, age*sex, and an intercept-only null model), 2) temporal variables (year, date, year+date), 3) spatial variables (latitude, longitude, latitude+longitude, and BCR), 4) mean percent impervious cover (over 1.859 km and 3.900 from migratory stop center), and 5) interactions between mean percent impervious cover and each of the other variables. In each round of model selection, the most supported model that had an effect with a p-value <0.05 for at least one level of the variable was carried forward and used as an additive effect at the next tier of model selection. Even if multiple models were supported at a tier with ΔAICc scores below 2.0, I only continued with the single best-supported model into the next tier. At tier four, I also ran models including percent impervious surface cover as the only predictor variable. In each round of selection except for tier one, the most supported model from the previous round of model selection was used as the null model. After model selection, I ran the supported models using the function "lm()" in program R (R core team 2023) for the Gaussian regressions to generate R^2 values and used the function "LogRegR2()" in the "descr" R package (Aquino et al. 2023) to generate McFadden's pseudo-R^2 values for the supported binary logistic models.

If two variables were correlated, I did not include them in the same model. If two correlated variables were in the same round of model selection, I didn't include a model with an additive effect between those two variables, and I only carried one or the other forward into the next round of model selection. If a variable from a previous round of model selection was correlated with a variable from the current round of model selection, I removed the previous correlated variable from that model only and ran the model selection otherwise unchanged. In cases where one variable that was part of an interactive effect needed to be removed from a model due to correlations, I decided whether to keep the second variable from the interaction that didn't have a correlation issue as an additive effect based on whether it was both supported (ΔAICc < 2.0 after the interactive model had been removed from the model selection), and had a significant effect (p-value < 0.05) when run on its own as part of its original tier of model selection. If it was, I removed the highly correlated variable and included the un-correlated variable as an additive effect, but if it wasn't, I included neither. All R code in support of my analysis (data preparation before and after I recieved the data, calculation of mean percent impervious surface cover, model selection, and post-hoc analysis and figure creation) is publicly available at https://github.com/EWMRC/Urbanization-and-migratory-behavior.

RESULTS

After data processing and removal of points with missing age and/or sex data, there were 694 stopping events from 173 individual birds in the fall and 623 stopping events from 124 individual birds in the spring. This data contained 198 stopping events by adult females, 175 stoppings events by young females, 156 stopping events by adult males, and 165 stopping events by young males in the fall, and 151 stopping events by adult females, 183 stopping events by young females, 124 stopping events by adult males, and 165 stopping events by young males in the spring. My analysis used 209 stopovers >1 day in length from 120 individual birds in the fall, and 268 stopovers >1 day from 114 individual birds in the spring. My analysis of migratory step distance included 521 migratory steps from 146 individual birds in the fall and 499 migratory steps from 113 individual birds in the spring.

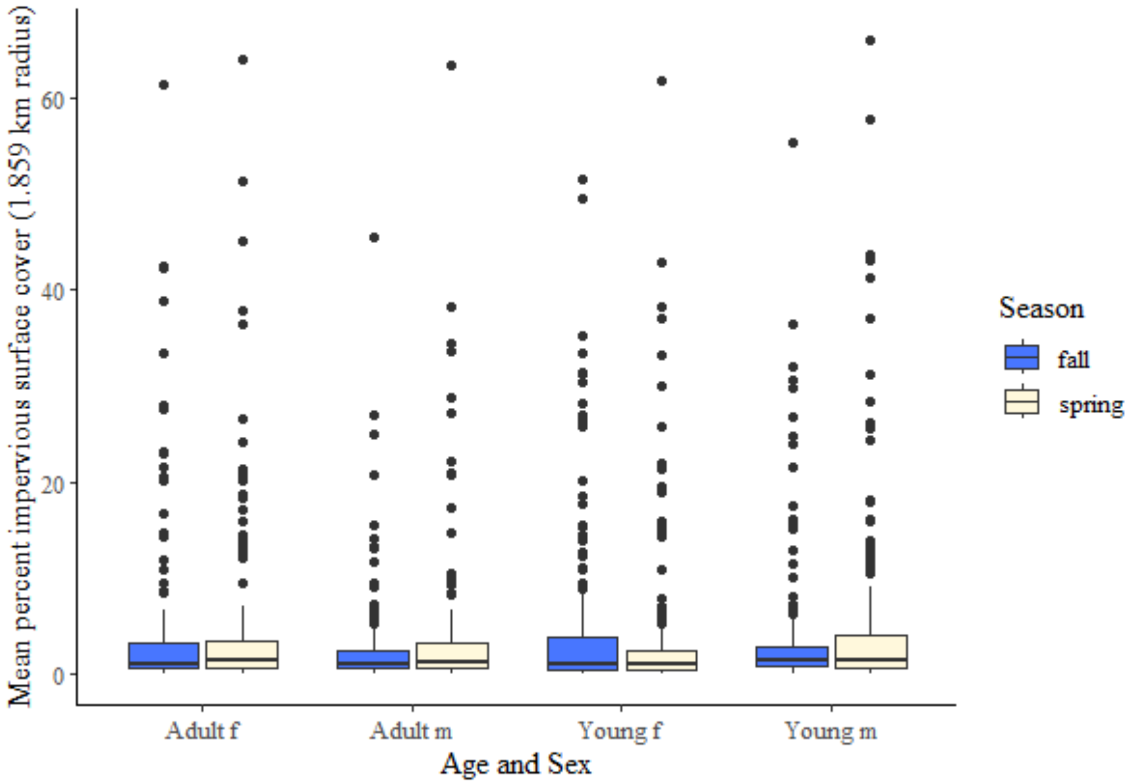

Figure 2. Distribution of mean percent impervious surface cover within 1.859 km of migratory stop center of American Woodcock by season and age-sex class. GPS-marked Woodcock were tracked migrating throughout eastern North America during 2017-2022. Figure created using the "ggplot2" package (Wickham 2016) in program R (R core team 2023).

The percent impervious surface cover within 1.859 km of stopping event center ranged from 0.00% to 61.49% in the fall, with a mean value of 3.90%, and ranged from 0.00% to 66.03% in the spring, with a mean value of .4.78%. The percent impervious surface cover within a 3.900 km of stopping event center ranged from .0091% to 61.89% in the fall, with a mean value of 4.01%, and ranged from 0.00% to 59.16% in the spring, with a mean value of 4.68% (Fig. 2-5). I found correlations between at least one set of variables used in each model run (Table 1) and did not include correlated pairs of variables in the same model. The data was skewed towards low percent impervious surface covers (Fig. 3); however, after exploring residual plots, I found that the data conformed to the assumption of normally distributed residuals required for a generalized linear model.

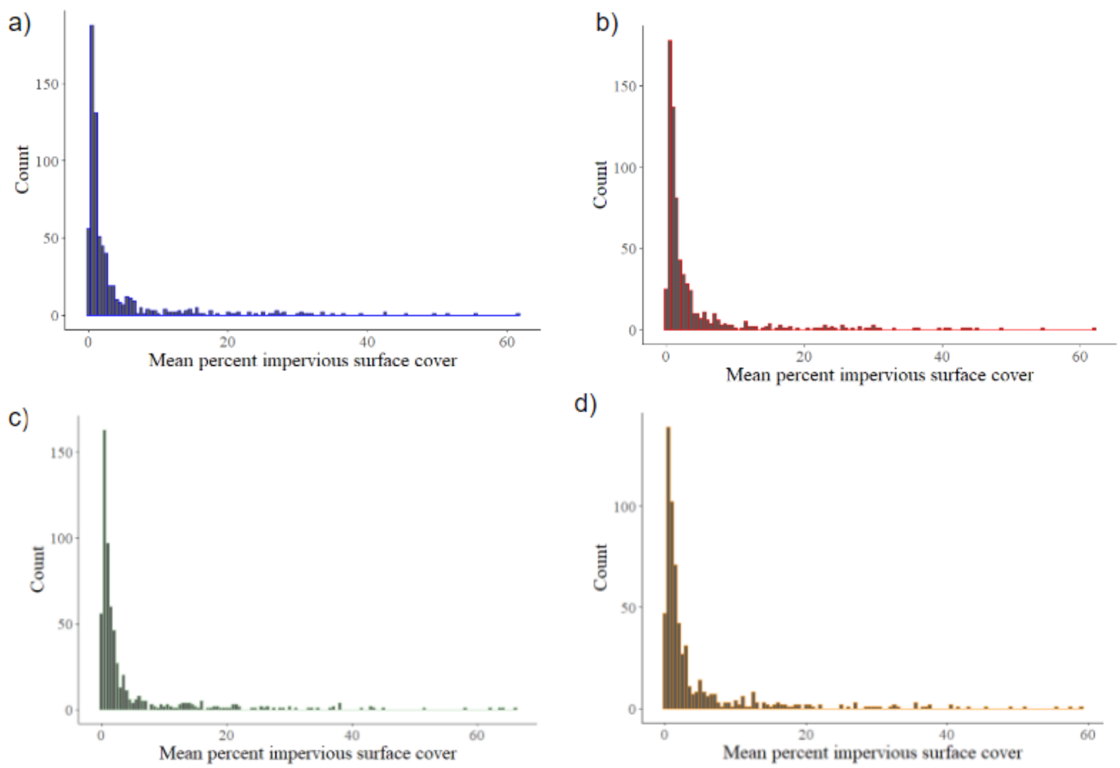

Figure 3. Distribution of percent impervious surface cover surrounding the migratory stopping events of GPS-marked Woodcock migrating throughout eastern North America during 2017-2022. a) mean percent impervious surface cover averaged over a 1.859 km radius from stopping event center in the fall, b) mean percent impervious surface cover averaged a 3.900 km radius from stopping event center in the fall, c) mean percent impervious surface cover averaged over a 1.859 km radius from stopping event center in the spring, and d) mean percent impervious surface cover averaged over a 3.900 km radius from stopping event center in the spring. Figure created using the "ggplot2" package (Wickham 2016) in program R (R core team 2023).

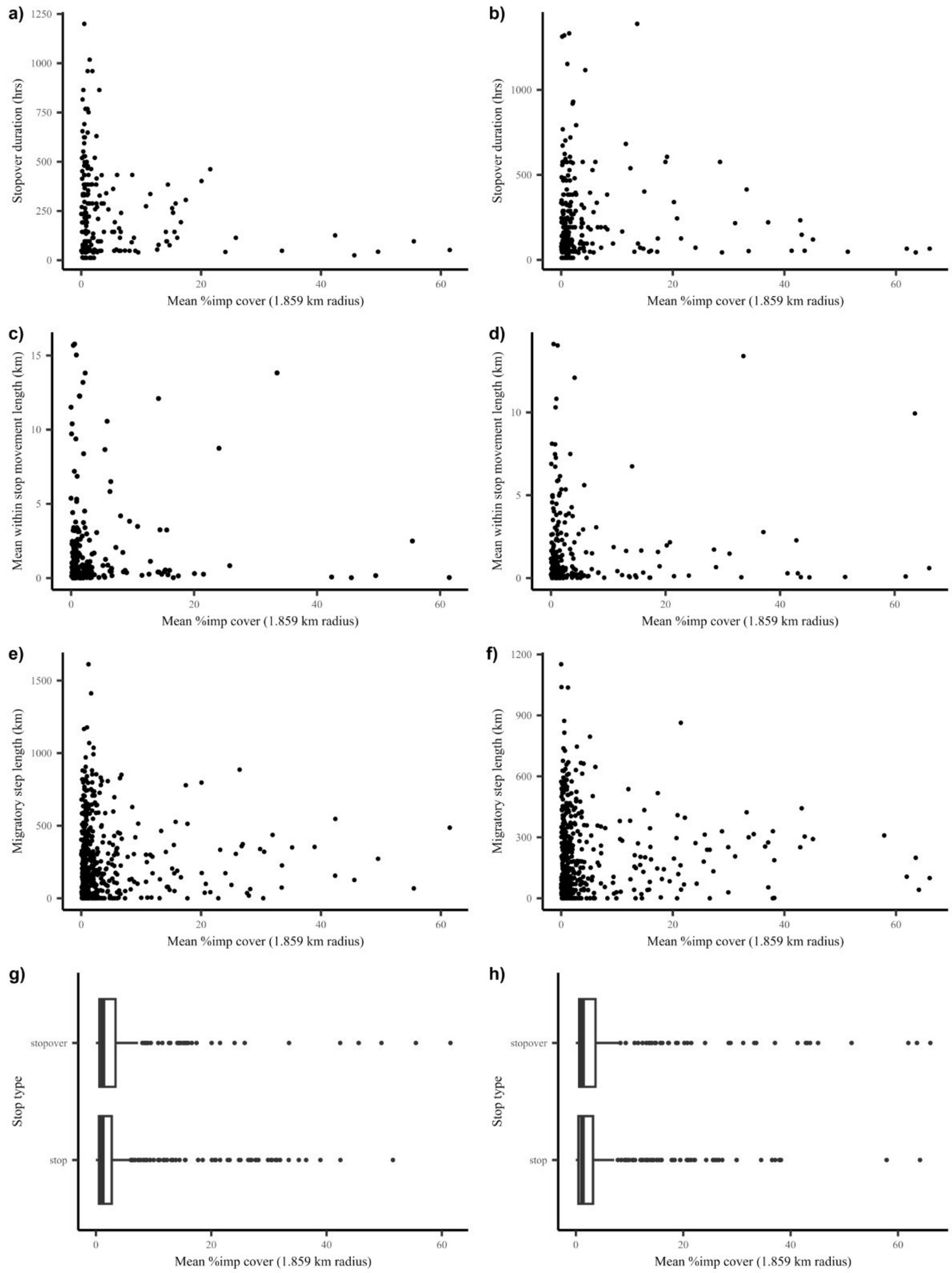

Figure 4. Migratory behavior of GPS-marked Woodcock migrating throughout eastern North America during 2017-2022 vs mean percent impervious surface cover within 1.859 km of stopping event. a) Duration of stopover, in hours, during fall migration, b) Duration of stopover, in hours, during spring migration, c) Mean within stopover movement distance, in km, during fall migration, d) Mean within stopover movement distance, in km, during spring migration, e) Subsequent migratory step distance, in km, during fall migration, f) Subsequent migratory step distance, in km, during spring migration, g) Stop type (<1 day "stop" or >1 day "stopover), during fall migration, and h) Stop type (<1 day "stop" or >1 day "stopover), during spring migration. Figure created using the "ggplot2" (Wickham 2016) and "cowplot" (Wilke 2024) packages in program R (R core team 2023).

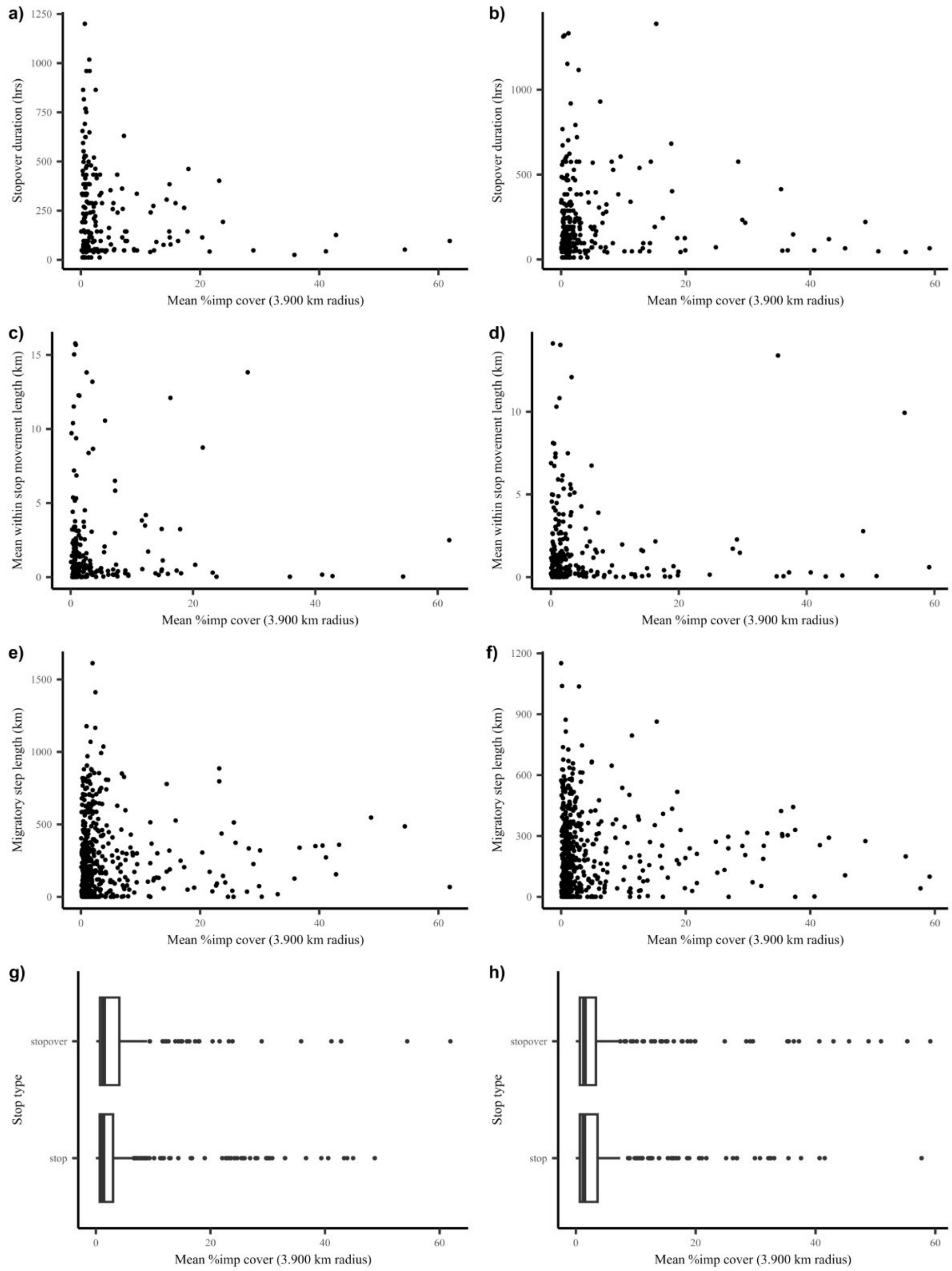

Figure 5. Migratory behavior of GPS-marked Woodcock migrating throughout eastern North America during 2017-2022 vs mean percent impervious surface cover within 3.900 km of stopping event. a) Duration of stopover, in hours, during fall migration, b) Duration of stopover, in hours, during spring migration, c) Mean within stopover movement distance, in km, during fall migration, d) Mean within stopover movement distance, in km, during spring migration, e) Subsequent migratory step distance, in km, during fall migration, f) Subsequent migratory step distance, in km, during spring migration, g) Stop type (<1 day “stop” or >1 day “stopover), during fall migration, and h) Stop type (<1 day “stop” or >1 day “stopover), during spring migration. Figure created using the “ggplot2” (Wickham 2016) and “cowplot” (Wilke 2024) packages in program R (R core team 2023).

	Stopover dataset	Full dataset	Step distance dataset
Fall	Year and BCR	Age and BCR Age and Year Sex and Year BCR and Year Latitude and Longitude	Age and BCR Age and Year Sex and Year BCR and Year
Spring	BCR and Sex Age and Year Latitude and Date	Age and BCR Sex and BCR Age and Year Sex and Year BCR and Year	Age and BCR Sex and BCR Age and Year Sex and Year BCR and Year

Table 1. Relationships among variables characterizing the migratory stopping events of GPS-tagged American Woodcock migrating through eastern North America between 2017 and 2023. I compared variables I planned to use as covariates in models predicting stopover behavior to assess correlations between them. The variables I tested were the age and sex of the bird, the year and date of the migratory stop, the latitude and longitude of the stop, and the bird conservation region (BCR) that the stop was in. I characterized two variables as correlated if they had a Chi-square or Fisher's exact test p-value of under 0.05 (for pairs of 2 categorical variables), a biserial or Pearson's correlation coefficient of over 0.7 (for pairs of one binary and on continuous variable or two continuous variables), and an R^2 score of 0.5 or more from a linear regression between each pair of one continuous and on non-binary categorical variable, as well as a p-value of under 0.05 for the effect of at least one level of the variable. I tested correlations in three different datasets I used for later analysis: the full dataset, a dataset subset to only include stopovers and not stops, and a dataset used for analyzing migratory step distance that only included stopping events with at least one later stop by the same bird.

Stopover Duration

For the fall, there were seven supported models predicting stopover duration (Table 2) The most supported model contained additive effects of year, date, latitude, and longitude and an interaction between impervious surface cover within 1.859 km of stopping event center and latitude (ΔAICc=0.00). See Supplementary Tables 1-2 for AICc tables of the model selection process. In the models containing individual, spatial, and temporal variables plus additive impervious surface effects, stopovers were shorter in areas with a greater percent impervious surface cover, with a 1% increase in mean impervious surface cover leading to a predicted 4.15 fewer hours of stopover time for the 1.859 km radius and a predicted 4.40 fewer hours for the 3.900 km radius. However, in both models, this effect was non-significant (p-value=0.067 for the 1.859 km radius and 0.075 for the 3.900 km radius). In the models including only the impervious surface variables, stopovers were shorter in areas with greater impervious surface cover and this effect was significant (a predicted 5.92 fewer hours of stopover per percent impervious surface cover over the 1.859 km radius with a p-value of 0.009, and a predicted 6.43 fewer stopover hours per percent impervious surface cover over the 3.900 km radius with a p-value of 0.009). However, neither of these models were supported once other potentially confounding variables were included. In both the interactive impervious surface cover*latitude and impervious surface cover*longitude models, neither the additive nor interactive impervious surface effect was significant in either model (Table 2). The best-supported model explained 10.3% of the variance in the data (adjusted R^2=0.103), and no other supported models explained a greater proportion of the variance (Table 2).

Δ AICc	K	Intercept	Year	Date	Lat.	Lon.	Imp. cover (1.859 km radius)	Imp. cover (3.900 km radius)	Imp. cover (1.859 km radius) * lat.	Imp. cover (3.900 km radius) * lat.	Imp. cover (1.859 km radius) * lon.	Imp. cover (3.900 km radius) * lon.	Adj. R^2
0.00	11	*-1215.146* (0.022)*	2021: *219.718* (0.008)*	*1.274* (0.011)*	*11.050* (0.089)	*-11.854* (0.007)*	*-52.398* (0.109)	N/A	*1.225* (0.139)	N/A	N/A	N/A	0.108
0.075	10	*-1260.520* (0.018)*	2021: *213.343* (0.001)*	*1.224* (0.015)*	*14.075* (0.023)*	*-11.0202* (0.012)*	*-4.1543* (0.067)	N/A	N/A	N/A	N/A	N/A	0.103
0.251	10	*-1242.336* (0.020)*	2021: *214.560* (0.001)*	*1.230* (0.014)*	*13.792* (0.026)*	*-10.939* (0.013)*	N/A	*-4.404* (0.075)	N/A	N/A	N/A	N/A	0.102
0.573	11	*-1197.819* (0.025)*	2021: *220.606* (>0.001)*	*1.270* (0.012)*	*10.916* (0.095)	*-11.709* (0.008)*	N/A	*-50.776* (0.142)	N/A	*1.182* (0.178)	N/A	N/A	0.106
1.378	9	*-1430.558* (0.007)*	2021: *227.397* (>0.001)*	*1.222* (0.016)*	*14.488* (0.020)*	-12.668 (0.003)*	N/A	N/A	N/A	N/A	N/A	N/A	0.920
1.507	11	*-1362.614* (0.013)*	2021: *213.759* (0.001)*	*1.241* (0.014)*	*13.823* (0.026)*	*-12.436* (0.008)*	*29.039* (0.447)	N/A	N/A	N/A	*0.436* (0.384)	N/A	0.102
1.876	11	*-1335.227* (0.015)*	2021: *215.260* (0.001)*	*1.247* (0.013)*	*13.519* (0.030)*	*-12.243* (0.010)*	N/A	*27.249* (0.515)	N/A	N/A	N/A	*0.416* (0.449)	0.010

Table 2. Coefficients and p-values for each variable in models predicting the duration, in hours, of stopovers of GPS tagged American Woodcock migrating in eastern North America in the fall between 2017 and 2022. All supported models (ΔAICc < 2.0) are shown from a model selection process including Woodcock age and sex, and stopover year, date, latitude, longitude, bird conservation region (BCR), and percent impervious surface cover averaged over two radii from stopover as predictor variables. Beta coefficients are shown in italics and p-values are shown in parentheses. An asterisk indicates that the effect is significant at an α level of 0.05. For the categorical year variable, results are only shown for the year with the largest significant effect, indicated before the colon.

For the spring, there were five supported models predicting stopover duration (Table 3). The most supported model contained age as the only predictor variable (ΔAICc=0.00). See supplementary Tables 3-4 for AICc tables of the model selection process. In the fifth supported model, stopovers with greater impervious surface cover within 1.859 km of stopover center were shorter, with a 1% increase in impervious surface cover leading to a predicted 1.78 fewer stopover hours, but this effect was non-significant (p-value=0.29). The impervious surface effect within 3.900 km of stopover center and all of the models with interactive impervious surface effects were not supported. The best-supported models explained 0.8% of the variance (adjusted R^2=0.008), and no supported model explained more than 0.9% of the variance (Table 3).

Delta AICc	K	Intercept	Age	Sex	Impervious cover (1.859 km radius)	Adjusted R^2
0.00	3	*223.32* (<0.001)*	Young: *56.38* (0.0775)	N/A	N/A	0.008
0.649	4	*241.93* (<0.001)*	Young: *58.07* (0.0691)	Male: -*37.23* (0.238)	N/A	0.009
1.101	2	*255.96* (<0.001)*	N/A	N/A	N/A	N/A
1.936	3	*274.190* (<0.001)*	N/A	Male: -*34.650* (0.273)	N/A	<0.001
1.993	3	*264.035* (<0.001)*	N/A	N/A	*-1.782* (0.285)	<0.001

Table 3. Coefficients and p-values for each variable in models predicting the duration, in hours, of stopovers of GPS tagged American Woodcock migrating in eastern North America in the spring between 2017 and 2022. All supported models (ΔAICc < 2.0) are shown from a model selection process including Woodcock age and sex, and stopover year, date, latitude, longitude, bird conservation region (BCR), and percent impervious surface cover averaged over two radii from stopover as predictor variables. Beta coefficients are shown in italics and p-values are shown in parentheses. An asterisk indicates that the effect is significant at an α level of 0.05.

Average Within Stopover Movement Distance

At tier three of my analysis for within stopover movement distance in the fall, the longitude effect was not significant (p-value= 0.123) but when longitude was not included (in the second-most-supported model, with additive effects of latitude and year, ΔAICc=0.30), the effect of latitude was no longer significant (p-value=0.104 in the model without longitude and 0.026 in the model with longitude). Because of this, I continued forward with the model containing both latitude and longitude in order to capture the significant effect of latitude. For the fall, two models predicting average within stopover movement distance were supported (Table 3). The most supported model (ΔAICc=0.00) contained additive effects of year, latitude, and longitude plus an interactive effect between year and mean percent impervious surface cover within 3.900 km of stopover center. See supplementary Tables 5-6 for AICc tables of the model selection process. The interaction between mean impervious surface cover and one year (2021) was significant in this model both within a 1.859 km radius and within a 3.900 km radius of stopover center, with impervious surface cover being significantly more positively associated with stopover movement distance in 2021 than in other years (Table 4, Figure 5). The best-supported models explained 10.8% of the variance (adjusted R^2=0.108), and no supported model explained a larger proportion of the variance (Table 4).

ΔAICc	K	Intercept	Year	Lat.	Lon.	Imp. cover (1.859 km radius)	Imp. cover (3.900 km radius)	Imp. cover (1.859 km radius) * year	Imp. cover (3.900 km radius) * year	Adj. R^2
0.00	13	*13.038* (0.064)	2022: *2.747* (0.033)*	*-0.161* (0.051)	*0.065* (0.267)	N/A	*-0.024* (0.587)	N/A	2021: *0.627* (<0.001)*	0.108
1.859	13	*13.411* (0.057)	2022: *2.811* (0.028)*	*-0.164* (0.047)*	*0.068* (0.245)	*-0.025* (0.552)	N/A	2021: *0.661* (<0.001)*	N/A	0.100

Table 4. Coefficients and p-values for each of the variables in supported models predicting average movement distance, in km within stopovers of GPS tagged American Woodcock migrating in eastern North America in the fall between 2017 and 2022. All supported models (ΔAICc < 2.0) are shown from a model selection process including Woodcock age and sex, and stopover year, date, latitude, longitude, bird conservation region (BCR), and percent impervious surface cover averaged over two radii from stopover as predictor variables. Beta coefficients are shown in italics and p-values are shown in parentheses. An asterisk indicates that the effect is significant at an α level of 0.05. For the categorical year variable, results are only shown for the year with the largest significant effect, indicated before the colon.

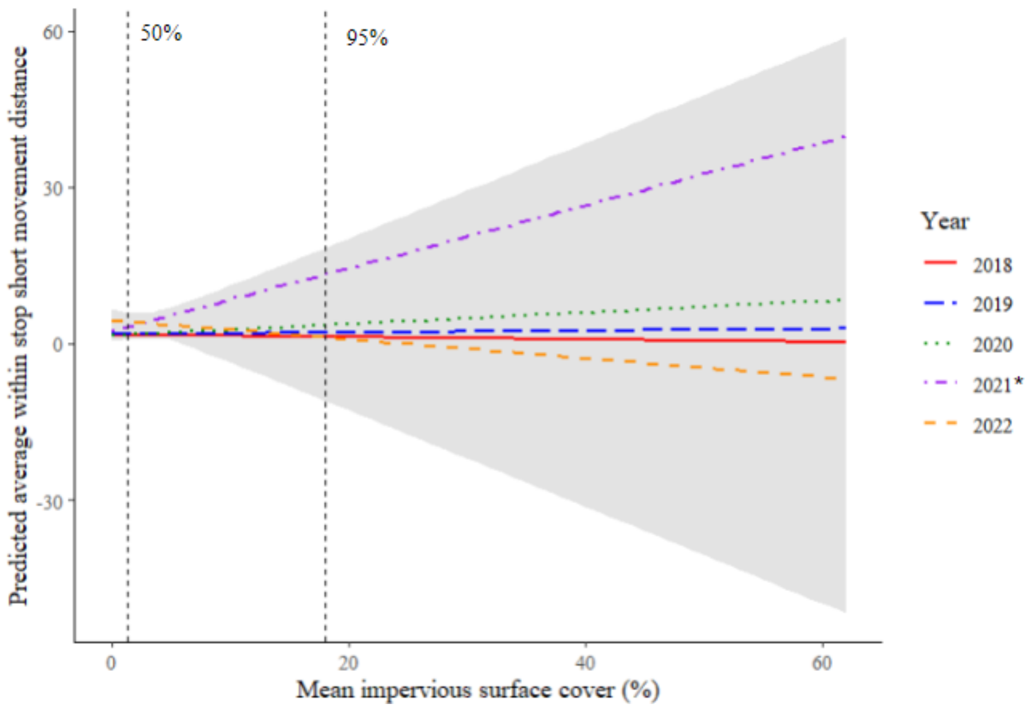

Figure 5. Average movement distance within the migratory stopovers of GPS-marked Woodcock migrating throughout eastern North America during 2017-2022, predicted from a model containing additive effects of year, latitude, and longitude, and an interactive effect of year and percent impervious surface cover within 1.859 km of stopover centroid. Latitude and longitude are held constant at their average values. The effect of impervious surface cover varies from year to year. The asterisk indicates a significant effect for the year 2021. The gray shaded region indicates the 95% confidence interval for the predicted values. The vertical dashed lines indicate the impervious surface cover values that 50% (left line) and 95% (right line) of stopover points fall beneath.

For the spring, there were six supported models predicting average within stopover movement distance (Table 5). The most supported model (ΔAICc=0.00) contained an additive effect of year and date. See supplementary Tables 7-8 for AICc tables of the model selection process. Mean within stopover step distances were slightly shorter in areas with greater impervious cover within 3.900 km of stopover center, with every 1% increase in mean impervious surface cover leading to a predicted 0.016 km shorter average within stopover step length, but this effect was non-significant (p-value=0.346). Similarly, mean within stopover step distances were slightly shorter in areas with greater impervious surface cover within a 1.859 km radius of stopping event center, with every 1% increase in mean impervious surface cover leading to a predicted 0.010 km shorter average within stopover step length, but this effect was non-significant (p-value=0.514). The most supported model explained 5.5% of the variance (adjusted R^2=0.055), and no other supported model explained a greater proportion of the variance (Table 5).

ΔAICc	K	Intercept	Year	Date	Lat.	Lon.	Imp. cover (1.859 km radius)	Imp. cover (3.900 km radius)	Adj. R^2
0.00	6	*-1.202* (0.509)	2022: *1.103* (0.018)*	*0.016* (0.127)	N/A	N/A	N/A	N/A	0.055
0.289	5	*1.546* (<0.001)*	2022: *1.036* (0.026)*	N/A	N/A	N/A	N/A	N/A	0.050
1.476	6	*1.621* (<0.001)*	2022: *1.046* (0.025)*	N/A	N/A	N/A	N/A	*-0.016* (0.346)	0.049
1.659	6	-0.194 (0.926)	2022: *1.047* (0.025)*	N/A	*0.042* (0.400)	N/A	N/A	N/A	0.049
1.817	6	*<0.001* (1.000)	2022: *1.0229* (0.028)*	N/A	N/A	*-0.020* (0.457)	N/A	N/A	0.048
1.946	6	*1.591* (<0.001)*	2022: *1.0544* (0.024)*	N/A	N/A	N/A	*-0.010* (0.514)	N/A	0.048

Table 5. Coefficients and p-values for each of the variables in supported models predicting average movement distance, in km, within stopovers of GPS tagged American Woodcock migrating in eastern North America in the spring between 2017 and 2022. All supported models (ΔAICc < 2.0) are shown from a model selection process including Woodcock age and sex, and stopover year, date, latitude, longitude, bird conservation region (BCR), and percent impervious surface cover averaged over two radii from stopping event as predictor variables. Beta coefficients are shown in italics and p-values are shown in parentheses. An asterisk indicates that the effect is significant at an α level of 0.05.

Stopping Event Type

In the fall, there were four supported models predicting stopping event type (Table 6). The most supported model (ΔAICc=0.00) was the intercept only model. See supplementary Tables 9-10 for AICc tables of the model selection process. No models with impervious surface effects were supported, the most supported being the model containing mean percent impervious surface cover within 1.859 km of stopping event center as the only predictor variable (ΔAICc= 2.01). No supported model had a McFadden's pseudo-R^2 value greater than 0.003 (Table 6).

ΔAICc	K	Intercept	Age	Sex	Date	McFadden's pseudo- R^2
0.000	1	*-0.756* (<0.001)*	N/A	N/A	N/A	N/A
1.577	2	*-0.665* (0.003)*	Young: -*0.187* (0.568)	N/A	N/A	0.002
1.648	2	*-0.721* (0.002)*	N/A	Male: -*0.070* (0.831)	N/A	>.001
1.747	2	*-0.461* (0.315)	N/A	N/A	*-0.007* (0.497)	0.003

Table 6. Coefficients and p-values for each of the variables in supported models predicting stopping event type (<1 day stop or > 1 day stopover) for migratory stopping events of GPS tagged American Woodcock migrating in eastern North America in the fall between 2017 and 2022. All supported models (ΔAICc < 2.0) are shown from a model selection process including Woodcock age and sex, and stopping event year, date, latitude, longitude, bird conservation region (BCR), and percent impervious surface cover averaged over two radii from stopping event as predictor variables. Beta coefficients are shown in italics and p-values are shown in parentheses. An asterisk indicates that the effect is significant at an α level of 0.05.

In the spring, there were six supported models predicting stopping event type (Table 7). The most supported model (ΔAICc= 0.00) was the intercept only model. See supplementary Tables 11-12 for AICc tables of the model selection process. Stopping events in areas with greater impervious surface cover within both 3.900 km and 1.859 km of migratory stop center were slightly more likely to be "stops", but this effect was non-significant (Table 7).

ΔAIC	K	Intercept	Age	Latitude	Longitude	Mean percent impervious surface cover within 1.859 km	Mean percent impervious surface cover within 3.900 km	McFadden's pseudo-R^2
0.00	1	*-0.150* (0.407)	N/A	N/A	N/A	N/A	N/A	N/A
1.348	2	*-0.313* (0.255)	Young: *0.289* (0.428)	N/A	N/A	N/A	N/A	0.004
1.858	2	*-1.743* (0.440)	N/A	*0.039* (0.478)	N/A	N/A	N/A	0.003
1.861	2	*-0.117* (0.567)	N/A	N/A	N/A	*-0.007* (0.737)	N/A	>.001
1.913	2	*-0.124* (0.552)	N/A	N/A	N/A	N/A	*-0.005* (0.807)	>.001
1.966	2	*-0.947* (0.720)	N/A	N/A	*-0.010* (0.762)	N/A	N/A	>0.001

Table 7. Coefficients and p-values for each of the variables in supported models predicting stopping event type (<1 day stop or > 1 day stopover) for migratory stopping events of GPS tagged American Woodcock migrating in eastern North America in the spring between 2017 and 2022. All supported models (ΔAICc < 2.0) are shown from a model selection process including Woodcock age and sex, and stopping event year, date, latitude, longitude, bird conservation region (BCR), and percent impervious surface cover averaged over two radii from stopover as predictor variables. Beta coefficients are shown in italics and p-values are shown in parentheses. An asterisk indicates that the effect is significant at an α level of 0.05.

Migratory Step Distance

In the fall, four models predicting migratory step distance were supported (Table 8). The most supported model (ΔAICc=0.00) contained additive effects of centroid latitude and mean percent impervious surface cover within 1.859 km of stopping event center. See supplementary Tables 13-14 for AICc tables of the model selection process. Stopping events in areas with greater impervious surface cover within 1.859 km of stopping event center had shorter subsequent migratory step distances, with a 1% increase in impervious surface cover leading to a predicted 2.51 km shorter subsequent migratory step distance, but this effect was non-significant (p-value=0.099). Similarly, stopping events in areas with greater impervious surface cover within 3.900 km of stopping event center had shorter subsequent migratory step distances, with a 1% increase in impervious surface cover leading to a predicted 2.088 km shorter subsequent migratory step length, but this effect was non-significant (p-value=0.166). The interactive effect between centroid latitude and mean percent impervious surface cover within 1.859 km of stopping event center was negative, with the association between impervious surface cover and migratory step length being more strongly positive at lower latitudes, but non-significant (Table 8). The most supported model explained 6.4% of the variance (adjusted R^2=0.064), and no other supported model explained a greater proportion of the variance (Table 8).

ΔAICc	K	Intercept	Latitude	Imp. cover (1.859 km radius)	Imp. cover (3.900 km radius)	Imp. cover (1.859 km radius) * latitude	Adjusted R^2
0.000	4	*-502.182* (<0.001)*	*20.750* (<0.001)*	*-2.511* (0.099)	N/A	N/A	0.064
0.706	3	*-488.862* (<0.001)*	*20.130* (<0.001)*	N/A	N/A	N/A	0.061
0.806	4	*-501.834* (<0.001)*	*20.701* (<0.001)*	N/A	*-2.088* (0.166)	N/A	0.062
1.886	5	*-530.063* (<0.001)*	*21.465* (<0.001)*	*6.672* (0.778)	N/A	*-0.232* (0.697)	0.062

Table 8. Coefficients and p-values for each of the variables in supported models predicting migratory step length for the migration legs following migratory stopping events of GPS tagged American Woodcock migrating in eastern North America in the fall between 2017 and 2022. All supported models (ΔAICc < 2.0) are shown from a model selection process including Woodcock age and sex, and stopping event year, date, latitude, longitude, bird conservation region (BCR), and percent impervious surface cover averaged over two radii from stopping events as predictor variables. Beta coefficients are shown in italics and p-values are shown in parentheses. An asterisk indicates that the effect is significant at an α level of 0.05.

At tier one of the migratory step length analysis in the spring, the effect of sex was not significant on its own (p-value= 0.065) but was significant in the age * sex interactive model (p-value- 0.01; the second-most-supported model ΔAICc=0.24). Because of this, I continued forward with the model containing the interactive effect between age and sex even though the interaction and the age effect in that model were non-significant (p-values = 0.095 and 0.633). Three models predicting after stopping event migratory step length in the spring were supported (Table 9). The most supported model (ΔAICc=0.00) contained an interactive effect of age and sex and additive effects of date, centroid latitude, and centroid longitude. See supplementary Tables 15-16 or

AICc tables of the model selection process. In the third supported model, the interaction between impervious surface cover and longitude was positive, with the association between impervious surface cover and migratory step length being more strongly positive at lower latitudes, but non-significant (Table 9). The most supported model explained 18.4% of the variance (adjusted $R^2 = 0.184$), and no other model explained a greater proportion of the variance.

ΔAICc	K	Intercept	Age	Sex	Age * Sex	Date	Lat.	Lon.	Imp. cover (3.900 km radius)	Imp. cover (3.900 km radius) * lon.	Adj. R^2
0.00	8	*1554.367* (<0.001)*	Young: *34.732* (0.156)	Male: *43.595* (0.096)	Young* Male: - *47.764* (0.166)	*1.916* (0.014)*	*-34.804* (< 0.001)*	*3.452* (0.062)	N/A	N/A	0.184
1.462	7	*1176.842* (<0.001)*	Young: *35.023* (0.154)	Male: *44.944* (0.087)	Young* Male: *-49.660* (0.150)	*1.869* (0.016)*	*-31.931* (<0.001)*	N/A	N/A	N/A	0.180
1.932	10	*1434.118* (<0.001)*	Young: *33.941* (0.166)	Male: *45.371* (0.083)	Young* Male: *-48.193* (0.162)	*2.065* (0.008)*	*-35.043* (< 0.001)*	*2.130* (0.300)	*22.519* (0.148)	*0.290* (0.154)	0.184

Table 9. Coefficients and p-values for each of the variables in supported models predicting migratory step length for the migration legs following migratory stops of GPS tagged American Woodcock migrating in eastern North America in the spring between 2017 and 2022. All supported models (ΔAICc < 2.0) are shown from a model selection process including Woodcock age and sex, and stopping event year, date, latitude, longitude, bird conservation region (BCR), and percent impervious surface cover averaged over two radii from stopover as predictor variables. Beta coefficients are shown in italics and p-values are shown in parentheses. An asterisk indicates that the effect is significant at an α level of 0.05. For the categorical year variable, results are only shown for the year with the largest significant effect, indicated before the colon.

DISCUSSION

I found little evidence to indicate that urbanization surrounding stopping sites has a dramatic effect on Woodcock migratory behavior. My hypotheses that stopovers with higher percent impervious surface covers would be shorter, more likely to be a stop as opposed to a stopover, have longer within stop flights, and have shorter migratory step lengths were not supported by my analysis. My results could indicate that stopovers in more urbanized areas do not provide less favorable stopover habitat for migrating Woodcock, or that Woodcock are able to manage the less favorable conditions of urban stopovers without compromising their migratory success. Some past studies have found a similar lack of effect of urbanization on migrating birds. Matthews and Rodewald (2010), for example, found no effect of urbanization on the stopover duration of migrating thrushes relocated during stopover to forest patches within a gradient of urbanization. Some bird species are able to persist and thrive in urban environments, and the characteristics associated with this ability have been a topic of past study. Bird species with a broad range of environmental tolerance are more likely to be successful in urban environments (Bonier et al. 2007). Other traits associated with birds that colonize urban environments may include a greater dispersal ability, ability to develop novel feeding strategies, low fear reaction to humans, larger immune defense organs, and high fecundity and adult survival (Møller 2009).

There was minimal evidence that urbanization affects Woodcock migration in a small number of supported models. The effect of impervious surface cover on average within stopover movement distance was different between fall migration seasons; in 2021, Woodcock had longer movement distances in areas of greater impervious surface cover, but there was no effect in other years. I included the year variable to account for variations between years in where and how many Woodcock were tagged, not because I expected that the effect of impervious surface cover on Woodcock migratory behavior would change over time. It is likely that the effect of year was due to differences in sampling year to year and does not represent a true biological effect of year on Woodcock migratory behavior. In the absence of any effect in other years, it is unlikely that the relationship shown in 2021 is a meaningful result. Additionally, model results approaching significance suggest a trend of shorter stopovers in areas with greater urbanization in the fall, indicating that there may be a negative effect of urbanization on migratory stopover duration that would become clearer at a larger sample size. If this were the case, it would indicate that Woodcock stop for shorter time periods in more urbanized areas, which could be a reflection of more urbanized sites having less favorable habitat and/or higher disturbance levels.

Notably, however, all supported Gaussian models had low adjusted R^2 values, with no supported model explaining more than 18.4% of the variance, and most supported models explaining under 11%. This indicates that none of the variables I used effectively explained most of the variation in Woodcock migratory behavior. Clements et al. (2024) found that Woodcock migratory behavior is diverse and does not conform to discrete strategies. Similarly, my results suggest that Woodcock migratory stopping behavior is variable and not well-explained by demographic factors, temporal and spatial variables, or human development. This diversity in migratory strategies may be a contributing factor to the lack of impervious surface effects on Woodcock migration, allowing them to respond with more flexibility to conditions during migration. Adjusted

R^2 values were also similar for all supported models within variables and seasons, indicating that no model explained much more of the variation in any variable than the other supported models (Tables 1-8).

One additional reason for the lack of support for an effect of urbanization may have been generally low levels of urbanization at most stopping locations. This may be proportional to the amount of sites with high impervious surface cover that Woodcock are likely to encounter on their migration or a result of random chance, but it is also possible that Woodcock avoid areas with high levels of urbanization which might otherwise adversely impact their migration success. Effects of urbanization on Woodcock migratory behavior may occur, but be minimized by Woodcock selecting stopping locations with lower levels of urbanization. In this case, the rare stopping events with the largest impervious surface covers would be expected to display a more marked difference in migratory behavior from most migratory stops. The maximum value for mean percent impervious surface cover was >60%; however, >95% of the stopping locations Woodcock used in the fall were in areas with <23% impervious surface cover, and >50% of stopping locations were in areas with <2% impervious surface cover. Patterns were similar in the spring, illustrating that in most cases, Woodcock used areas with relatively low impervious surface cover and hence were not exposed to the greatest levels of urbanization.

While my results do not show effects of urbanization across the whole dataset, post-hoc examination of the data points with high impervious surface covers suggests some evidence that urbanization may negatively affect Woodcock migration above a certain threshold. For example, while the mean stopover duration in my dataset in the fall was 232 hours, the maximum value was 1,200 hours. All values of over 500 hours (22 points) occurred at sites with mean percent impervious surface covers of under 3.015% for the 1.859 km radius, and no point with a mean percent impervious surface cover above 22% for the 1.859 km radius (8 points) had durations of 126 hours or shorter. Other variables show similar patterns (see Figs. 4 and 5), which could indicate a potential threshold effect, where urbanization does not have a significant effect on Woodcock stopping events until it reaches a critical point. Threshold effects of urbanization on birds have been found in the past (DeLuca et al. 2008). Understanding important thresholds for effects of urbanization on wildlife can be key to informing recommendations for conservation and habitat management (Bradsworth et al. 2022). Future research documenting and quantifying potential thresholds for the effects of urbanization on Woodcock could contribute important information for the conservation of the species.

However, it is also possible that Woodcock respond to greater urbanization of their migratory stopover sites in ways that are not measured by the four variables I chose to analyze. Less favorable stopping conditions may not result in shorter stops, a greater likelihood of a migratory stop vs stopover, a longer average within stop movement distance, or shorter after stop migratory step lengths. Other measures, such as body condition and mortality, could better reflect effects of urbanization on migrating Woodcock. For example, I did not attempt to estimate mortality from the GPS tag data because mortality is very difficult to distinguish from a transmitter being dropped or running out of battery power. Additionally, the window in between when locations were collected would have made it difficult to accurately connect mortality to a particular cause. Collision with windows is one potential source of mortality in urban environments; however, mortality from window strikes may actually be highest for large buildings in less urbanized areas (Hager et al. 2017).

Additionally, because locations were only recorded every 1-2 days, the exact timing and location of migratory stops may not have been recorded with complete accuracy. This could introduce error, particularly for the short movements within stopover, which likely occurred at a finer temporal and spatial scale that may have been more vulnerable to being missed or altered because of the delay in point captures.

My results do not support the idea that more urbanized areas provide less favorable stopping sites for migrating Woodcock, at least at lower levels of urbanization. Whether this is because of a lack of effect of urbanization on migrating Woodcock or because they are able to manage urban effects through selection of stopping sites or smaller-scale behavioral modifications, my results suggest that Woodcock may be resilient to urbanized development within their migratory range. Alternatively, I found some evidence of potential threshold effects of urbanization on Woodcock migratory behavior, and this could be an avenue for future study.

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APPENDICES

Appendix A: Supplementary AICc tables

	Model	K	AICc	ΔAICc	AICc weight	Cumulative weight	Log-Likelihood
Tier 1	**Null**	**2**	**2924.39**	**0.00**	**0.48**	**0.48**	**-1460.17**
	Age	3	2925.97	1.57	0.22	0.70	-1459.92
	Sex	3	2926.34	1.95	0.18	0.89	-1460.11
	Age + Sex	4	2927.98	3.59	0.08	0.97	-1459.89
	Age*Sex	5	2929.66	5.27	0.03	1.00	-1459.68
Tier 2	**Year + Date**	**7**	**2917.00**	**0.00**	**0.69**	**0.69**	**-1451.22**
	Year	6	2919.23	2.23	0.23	0.92	-1453.41
	Date	3	2921.67	4.67	0.07	0.98	-1457.78
	Null	2	2924.39	7.39	0.02	1.00	-1460.17
Tier 3	**Year + Date + Lat + Lon**	**9**	**2911.92**	**0.00**	**0.76**	**0.76**	**-1446.51**
	Year + Date + Lon	8	2915.36	3.44	0.14	0.89	-1449.32
	Year + Date	7	2917.00	5.08	0.06	0.95	-1451.22
	Year + Date + Lat	8	2918.66	6.75	0.03	0.98	-1450.97
	Date + BCR	9	2919.00	7.09	0.02	1.00	-1450.05

Supplementary Table 1. AICc selection process for linear models predicting the duration, in hours, of migratory stopovers for GPS tagged American Woodcock migrating in eastern North America in the fall between 2017 and 2022. A tiered model selection approach was used to establish the most supported combination of individual, spatial, and temporal variables, where the most supported model (lowest ΔAICc score) that also had an effect for all variables that was significant at an α of 0.05 was carried forward as an additive effect in the next tier. The models that were carried forward are shown in bold. The most supported model at tier three was used to account for confounding variables in tests of additive and interactive effects of impervious surface cover on stopover duration. “BCR” refers to bird conservation region. The null model is an intercept-only model.

Model	K	AICc	ΔAICc	Model Likelihood	AICc Weight	Log-Likelihood	Cumulative Weight
Year + Date + Lat + Lon + Imp1.859*Lat	11	2910.54	0.00	1.00	0.16	-1443.60	0.16
Year + Date + Lat + Lon + Imp1.859	10	2910.61	0.08	0.96	0.15	-1444.75	0.30
Year + Date + Lat + Lon + Imp3.900	10	2910.79	0.25	0.88	0.14	-1444.84	0.44
Year + Date + Lat + Lon + Imp3.900*Lat	11	2911.11	0.57	0.75	0.12	-1443.89	0.56
Year + Date + Lat + Lon	9	2911.92	1.38	0.50	0.08	-1446.51	0.64
Year + Date + Lat + Lon + Imp1.859*Lon	11	2912.05	1.51	0.47	0.07	-1444.35	0.71
Year + Date + Lat + Lon + Imp3.900*Lon	11	2912.41	1.88	0.39	0.06	-1444.54	0.77
Year + Date + Lat + Lon + Imp1.859*date	11	2912.66	2.12	0.35	0.05	-1444.66	0.82
Year + Date + Lat + Lon + Imp3.900*Date	11	2912.76	2.22	0.33	0.05	-1444.71	0.87
Year + Date + Lat + Lon + Imp1.859*Age	12	2914.32	3.79	0.15	0.02	-1444.37	0.90
Year + Date + Lat + Lon + Imp3.900*Age	12	2914.46	3.92	0.14	0.02	-1444.43	0.92
Year + Date + Lat + Lon + Imp3.900*Sex	12	2914.92	4.38	0.11	0.02	-1444.66	0.94
Year + Date + Lat + Lon + Imp1.859*Sex	12	2914.93	4.39	0.11	0.02	-1444.67	0.95
Year + Date + Lon	8	2915.36	4.82	0.09	0.01	-1449.32	0.97
Year + Date + Lat + Lon + Imp3.900*Year	14	2916.51	5.97	0.05	0.01	-1443.17	0.98

Year + Date + Lat + Lon + Imp1.859*Year	14	2916.94	6.40	0.04	0.01	-1443.39	0.98
Year + Date	7	2917.00	6.46	0.04	0.01	-1451.22	0.99
Year + Date + Lat	8	2918.66	8.12	0.02	0.00	-1450.97	0.99
Date + BCR	9	2919.00	8.46	0.01	0.00	-1450.05	0.99
Year	6	2919.23	8.69	0.01	0.00	-1453.41	1.00
Imp1.859	3	2919.63	9.09	0.01	0.00	-1456.76	1.00
Imp3.900	3	2919.63	9.09	0.01	0.00	-1456.76	1.00
Date	3	2921.67	11.13	0.00	0.00	-1457.78	1.00
Null	2	2924.39	13.85	0.00	0.00	-1460.17	1.00
Age	3	2925.97	15.43	0.00	0.00	-1459.92	1.00
Sex	3	2926.34	15.81	0.00	0.00	-1460.11	1.00
Age + Sex	4	2927.98	17.44	0.00	0.00	-1459.89	1.00
Date + Imp3.900*BCR	16	2928.16	17.62	0.00	0.00	-1446.66	1.00
Date + Imp1.859*BCR	16	2928.38	17.84	0.00	0.00	-1446.77	1.00
Age*Sex	5	2929.66	19.12	0.00	0.00	-1459.68	1.00

Supplementary Table 2. AICc results for generalized linear models predicting the duration, in hours, of migratory stopovers of GPS-tagged American Woodcock migrating through eastern North America in the fall of 2017-2022. “Imp1.859” refers to mean percent impervious surface cover within 1.859 km of stopover center, and “Imp3.900” refers to mean percent impervious surface cover within 3.900 km of stopover center. “BCR” refers to bird conservation region. The null model is an intercept-only model.

	Model	K	AICc	ΔAICc	AICc Weight	Cumulative Weight	Log-Likelihood
Tier 1	Age	3	3782.37	0.00	0.34	0.34	-1888.14
	Age + Sex	4	3783.02	0.65	0.25	0.59	-1887.43
	Null	**2**	**3783.47**	**1.10**	**0.20**	**0.78**	**-1889.71**
	Sex	3	3784.31	1.94	0.13	0.91	-1889.11
	Age*Sex	5	3785.10	2.72	0.09	1.00	-1887.43
Tier 2	**Null**	**2**	**3783.47**	**0.00**	**0.59**	**0.59**	**-1889.71**
	Date	3	3784.42	0.95	0.36	0.95	-1889.17
	Year	5	3789.33	5.86	0.03	0.98	-1889.55
	Year + Date	6	3790.35	6.88	0.02	1.00	-1889.02
Tier 3	**Null**	**2**	**3783.47**	**0.00**	**0.40**	**0.40**	**-1889.71**
	Latitude	3	3784.71	1.24	0.22	0.62	-1889.31
	Longitude	3	3785.45	1.98	0.15	0.77	-1889.68
	BCR	8	3785.78	2.31	0.13	0.90	-1884.61
	Latitude + Longitude	4	3786.21	2.74	0.10	1.00	-1889.03

Supplementary Table 3. AICc selection process for linear models predicting the duration, in hours, of migratory stopovers for GPS tagged American Woodcock migrating in eastern North America in the spring between 2017 and 2022. A tiered model selection approach was used to establish the most supported combination of individual, spatial, and temporal variables, where the most supported model (lowest ΔAICc score) that also had an effect for all variables that was significant at an α of 0.05 was carried forward as an additive effect in the next tier. The models that were carried forward are shown in bold. The most supported model at tier three was used to account for confounding variables in tests of additive and interactive effects of impervious surface cover on stopover duration. "BCR" refers to bird conservation region. The null model is an intercept-only model.

Model	K	AICc	ΔAICc	Model Likelihood	AICc Weight	Log-Likelihood
Age	3	3782.37	0.00	1.00	0.16	-1888.14
Age + Sex	4	3783.02	0.65	0.72	0.12	-1887.43
Null	2	3783.47	1.10	0.58	0.09	-1889.71
Sex	3	3784.31	1.94	0.38	0.06	-1889.11
Imp1.859	3	3784.36	1.99	0.37	0.06	-1889.14
Date	3	3784.42	2.05	0.36	0.06	-1889.17
Lat	3	3784.71	2.34	0.31	0.05	-1889.31
Imp3.900	3	3784.92	2.55	0.28	0.05	-1889.41
Imp3.900*Age	5	3784.95	2.58	0.28	0.04	-1887.36
Imp1.859*Age	5	3784.97	2.60	0.27	0.04	-1887.37
Age*Sex	5	3785.10	2.72	0.26	0.04	-1887.43
Lon	3	3785.45	3.08	0.21	0.03	-1889.68
BCR	8	3785.78	3.41	0.18	0.03	-1884.61
Imp1.859*Lat	5	3785.84	3.47	0.18	0.03	-1887.81
Imp3.900*Lat	5	3786.11	3.74	0.15	0.03	-1887.94
Lat + Lon	4	3786.21	3.84	0.15	0.02	-1889.03
Imp1.859*Sex	5	3787.08	4.71	0.09	0.02	-1888.42
Imp1.859*Date	5	3787.44	5.07	0.08	0.01	-1888.60
Imp3.900*Sex	5	3787.44	5.07	0.08	0.01	-1888.61
Imp3.900*Date	5	3787.79	5.42	0.07	0.01	-1888.78
Imp3.900*Lon	5	3788.02	5.65	0.06	0.01	-1888.89
Imp1.859* Lon	5	3788.15	5.78	0.06	0.01	-1888.96
Year	5	3789.33	6.96	0.03	0.01	-1889.55
Year + Date	6	3790.35	7.98	0.02	0.00	-1889.02
Imp1.859*Year	9	3795.72	13.35	0.00	0.00	-1888.51

Imp3.900*Year	9	3796.05	13.68	0.00	0.00	-1888.68
Imp1.859*BCR	15	3798.90	16.53	0.00	0.00	-1883.50
Imp3.900*BCR	15	3799.68	17.31	0.00	0.00	-1883.89

Supplementary Table 4. AICc results for generalized linear models predicting the average duration, in hours, of migratory stopovers of GPS-tagged American Woodcock migrating through eastern North America in the spring of 2017-2022. “Imp1.859” refers to mean percent impervious surface cover within 1.859 km of stopover center, and “Imp3.900” refers to mean percent impervious surface cover within 3.900 km of stopover center. “BCR” refers to bird conservation region. The null model is an intercept-only model.

	Model	K	AICc	ΔAICc	AICc Weight	Cumulative Weight	Log-Likelihood
Tier 1	**Null**	**2**	**1121.22**	**0.00**	**0.53**	**0.53**	**-558.58**
	Sex	3	1123.22	1.99	0.19	0.72	-558.55
	Age	3	1123.28	2.06	0.19	0.91	-558.58
	Age + Sex	4	1125.29	4.07	0.07	0.98	-558.55
	Age * Sex	5	1127.39	6.17	0.02	1.00	-558.55
Tier 2	**Year**	**6**	**1116.29**	**0.00**	**0.65**	**0.65**	**-551.94**
	Year + Date	7	1118.05	1.76	0.27	0.92	-551.75
	Null	2	1121.22	4.93	0.06	0.98	-558.58
	Date	3	1123.00	6.71	0.02	1.00	-558.44
Tier 3	**Year + Latitude + Longitude**	**8**	**1115.40**	**0.00**	**0.30**	**0.30**	**-549.34**
	Year + Latitude	7	1115.70	0.30	0.26	0.57	-550.57
	Year	6	1116.29	0.89	0.19	0.76	-551.94
	BCR	8	1116.56	1.16	0.17	0.93	-549.92
	Year + Longitude	7	1118.36	2.96	0.07	1.00	-551.90

Supplementary Table 5. AICc selection process for linear models predicting the average movement distance, in km, within the stopovers of GPS tagged American Woodcock migrating in eastern North America in the fall between 2017 and 2022. A tiered model selection approach was used to establish the most supported combination of individual, spatial, and temporal variables, where the most supported model (lowest ΔAICc score) that also had an effect for all variables that was significant at an α of 0.05 was carried forward as an additive effect in the next tier. The models that were carried forward are shown in bold. The most supported model at tier three was used to account for confounding variables in tests of additive and interactive effects of impervious surface cover on average within stopover movement distance. "BCR" refers to bird conservation region. The null model is an intercept-only model.

Model	K	AICc	ΔAICc	Model Likelihood	AICc Weight	Log-Likelihood	Cumulative Weight
Year + Lat + Lon + Imp3.900*Year	13	1109.72	0.00	1.00	0.56	-540.93	0.56
Year + Lat + Lon + Imp1.859*Year	13	1111.58	1.86	0.39	0.22	-541.86	0.78
Year + Lat + Lon	8	1115.40	5.68	0.06	0.03	-549.34	0.81
Year + Lat	7	1115.70	5.98	0.05	0.03	-550.57	0.84
Year	6	1116.29	6.57	0.04	0.02	-551.94	0.86
BCR	8	1116.56	6.84	0.03	0.02	-549.92	0.88
Year + Lat + Lon + Imp3.900	9	1116.60	6.88	0.03	0.02	-548.85	0.90
Year + Lat + Lon + Imp1.859	9	1116.92	7.20	0.03	0.02	-549.01	0.91
Year + Lat + Lon + Imp1.859*Lat	10	1117.11	7.38	0.02	0.01	-548.00	0.92
Year + Lat + Lon + Imp3.900*Lat	10	1117.18	7.46	0.02	0.01	-548.03	0.94
Year + Lat + Lon + Imp3.900*Lon	10	1117.82	8.10	0.02	0.01	-548.36	0.95
Year + Lat + Lon + Imp1.859*Lon	10	1117.94	8.21	0.02	0.01	-548.41	0.96
Year + Date	7	1118.05	8.33	0.02	0.01	-551.75	0.97
Year + Lon	7	1118.36	8.63	0.01	0.01	-551.90	0.97
Year + Lat + Lon + Imp3.900*Sex	11	1119.14	9.42	0.01	0.01	-547.90	0.98
Year + Lat + Lon + Imp1.859*Sex	11	1119.69	9.97	0.01	0.00	-548.18	0.98

Year + Lat + Lon + Imp3.900*Date	11	1119.70	9.97	0.01	0.00	-548.18	0.99
Year + Lat + Lon + Imp1.859*Date	11	1119.75	10.03	0.01	0.00	-548.21	0.99
Year + Lat + Lon + Imp3.900*Age	11	1120.44	10.71	0.00	0.00	-548.55	0.99
Year + Lat + Lon + Imp1.859*Age	11	1120.55	10.83	0.00	0.00	-548.61	0.99
Null	2	1121.22	11.50	0.00	0.00	-558.58	1.00
Imp3.900	3	1122.72	13.00	0.00	0.00	-558.30	1.00
Date	3	1123.00	13.28	0.00	0.00	-558.44	1.00
Imp1.859	3	1123.02	13.30	0.00	0.00	-558.45	1.00
Sex	3	1123.22	13.49	0.00	0.00	-558.55	1.00
Age	3	1123.28	13.56	0.00	0.00	-558.58	1.00
Age + Sex	4	1125.29	15.57	0.00	0.00	-558.55	1.00
Age*Sex	5	1127.39	17.67	0.00	0.00	-558.55	1.00
Imp1859*BCR	15	1129.02	19.30	0.00	0.00	-548.27	1.00
Imp3.900*BCR	15	1129.29	19.56	0.00	0.00	-548.40	1.00

Supplementary Table 6. AICc results for generalized linear models predicting the average movement distance, in km, within migratory stopovers of GPS-tagged American Woodcock migrating through eastern North America in the fall of 2017-2022. "Imp1.859" refers to mean percent impervious surface cover within 1.859 km of stopover center, and "Imp3.900" refers to mean percent impervious surface cover within 3.900 km of stopover center. "BCR" refers to bird conservation region. The null model is an intercept-only model.

	Model	K	AICc	ΔAICc	AICc Weight	Cumulative Weight	Log-Likelihood
Tier 1	**Age * Sex**	**5**	**1271.27**	**0.00**	**0.44**	**0.44**	**-630.52**
	Sex	3	1272.30	1.03	0.26	0.70	-633.10
	Null	2	1273.42	2.15	0.15	0.85	-634.69
	Age + Sex	4	1274.28	3.00	0.10	0.94	-633.06
	Age	3	1275.33	4.06	0.06	1.00	-634.62
Tier 2	Year + Date	6	1262.60	0.00	0.52	0.52	-625.14
	Year	**5**	**1262.89**	**0.29**	**0.45**	**0.97**	**-626.33**
	(Age*Sex) + Date	6	1268.68	6.08	0.02	0.99	-628.18
	Age * Sex	5	1271.27	8.67	0.01	1.00	-630.52
Tier 3	**Year**	**5**	**1262.89**	**0.00**	**0.40**	**0.40**	**-626.33**
	Year + Latitude	6	1264.26	1.37	0.20	0.60	-625.97
	Year + Longitude	6	1264.42	1.53	0.19	0.78	-626.05
	Year + Latitude + Longitude	7	1264.76	1.87	0.16	0.94	-625.17
	Year + BCR	11	1266.68	3.78	0.06	1.00	-621.82

Supplementary Table 7. AICc selection process for linear models predicting the average movement distance, in km, within the stopovers of GPS tagged American Woodcock migrating through eastern North America in the spring between 2017 and 2022. A tiered model selection approach was used to establish the most supported combination of individual, spatial, and temporal variables, where the most supported model (lowest ΔAICc score) that also had an effect for all variables that was significant at an α of 0.05 was carried forward as an additive effect in the next tier. The models that were carried forward are shown in bold. The most supported model at tier three was used to account for confounding variables in tests of additive and interactive effects of impervious surface cover on average within stopover movement distance. "BCR" refers to bird conservation region. The null model is an intercept-only model.

Model	K	AICc	ΔAICc	Model Likelihood	AICc Weight	Log-Likelihood	Cumulative Weight
Year + Date	6	1262.60	0.00	1.00	0.18	-625.14	0.18
Year	5	1262.89	0.29	0.87	0.15	-626.33	0.33
Year + Imp3.900	6	1264.08	1.48	0.48	0.08	-625.88	0.41
Year + Lat	6	1264.26	1.66	0.44	0.08	-625.97	0.49
Year + Lon	6	1264.42	1.82	0.40	0.07	-626.05	0.56
Year + Imp1.859	6	1264.55	1.95	0.38	0.07	-626.11	0.63
Year + Lat + Lon	7	1264.76	2.16	0.34	0.06	-625.17	0.69
Year + Imp3.900*Date	8	1265.21	2.61	0.27	0.05	-624.33	0.73
Year + Imp3.900*Sex	8	1265.55	2.94	0.23	0.04	-624.50	0.77
Year + Imp3.900*Lon	8	1265.74	3.14	0.21	0.04	-624.59	0.81
Year + Imp1.859*Sex	8	1265.81	3.21	0.20	0.04	-624.63	0.85
Year + 1.859*Date	8	1266.25	3.65	0.16	0.03	-624.85	0.88
Year + Imp3.900*Lat	8	1266.36	3.76	0.15	0.03	-624.90	0.90
Year + Imp1.859*Lon	8	1266.61	4.00	0.14	0.02	-625.02	0.93
Year + BCR	11	1266.68	4.07	0.13	0.02	-621.82	0.95
Year + 1.859*Lat	8	1267.68	5.08	0.08	0.01	-625.56	0.96
Year + Imp3.900*Year	9	1268.33	5.72	0.06	0.01	-624.81	0.97
Year + Imp1.859*Year	9	1268.58	5.98	0.05	0.01	-624.94	0.98
Age*Sex + Date	6	1268.68	6.08	0.05	0.01	-628.18	0.99
Age*Sex	5	1271.27	8.67	0.01	0.00	-630.52	0.99
Year + Imp3.900*BCR	18	1271.43	8.83	0.01	0.00	-616.34	0.99

Year + Imp1.859*BCR	18	1272.00	9.39	0.01	0.00	-616.62	1.00
Sex	3	1272.30	9.70	0.01	0.00	-633.10	1.00
Null	2	1273.42	10.82	0.00	0.00	-634.69	1.00
Age + Sex	4	1274.28	11.67	0.00	0.00	-633.06	1.00
Imp3.900	3	1274.99	12.39	0.00	0.00	-634.45	1.00
Age	3	1275.33	12.73	0.00	0.00	-634.62	1.00
Imp1.859	3	1275.41	12.80	0.00	0.00	-634.66	1.00
Imp1.859*Age	5	1275.74	13.14	0.00	0.00	-632.75	1.00
Imp3.900*Age	5	1276.54	13.94	0.00	0.00	-633.16	1.00

Supplementary Table 8. AICc results for generalized linear models predicting the average movement distance, in km, within migratory stopovers of GPS-tagged American Woodcock migrating through eastern North America in the spring of 2017-2022. "Imp1.859" refers to mean percent impervious surface cover within 1.859 km of stopover center, and "Imp3.900" refers to mean percent impervious surface cover within 3.900 km of stopover center. "BCR" refers to bird conservation region. The null model is an intercept-only model.

	Model Name	K	AICc	ΔAICc	AICc Weight	Cumulative Weight	Log-Likelihood
Tier 1	**Null**	**1**	**39.42**	**0.00**	**0.47**	**0.47**	**-18.71**
	Age	2	41.00	1.58	0.21	0.68	-18.49
	Sex	2	41.07	1.65	0.20	0.88	-18.53
	Age + Sex	3	42.81	3.39	0.09	0.97	-18.39
	Age* Sex	4	44.82	5.40	0.03	1.00	-18.38
Tier 2	**Null**	**1**	**39.42**	**0.00**	**0.69**	**0.69**	**-18.71**
	Date	2	41.17	1.75	0.29	0.98	-18.58
	Year	6	47.55	8.13	0.01	0.99	-17.71
	Year + Date	7	49.14	9.72	0.01	1.00	-17.49
Tier 3	**Null**	**1**	**39.42**	**0.00**	**0.61**	**0.61**	**-18.71**
	Longitude	2	41.45	2.03	0.22	0.83	-18.72
	Latitude	2	42.08	2.65	0.16	1.00	-19.03
	BCR	7	49.38	9.96	0.00	1.00	-17.61

Supplementary Table 9. AICc selection process for linear models predicting the stop type (<1 day "stop" or >1 day "stopover) of the migratory stopping events of GPS tagged American Woodcock migrating through eastern North America in the fall between 2017 and 2022. A tiered model selection approach was used to establish the most supported combination of individual, spatial, and temporal variables, where the most supported model (lowest ΔAICc score) that also had an effect for all variables that was significant at an α of 0.05 was carried forward as an additive effect in the next tier. The models that were carried forward are shown in bold. The most supported model at tier three was used to account for confounding variables in tests of additive and interactive effects of impervious surface cover on stopping event type. "BCR" refers to bird conservation region. The null model is an intercept-only model.

Model Name	K	AICc	ΔAICc	Model Likelihood	AICc Weight	Log-Likelihood	Cumulative Weight
Null	1	39.42	0.00	1.00	0.22	-18.71	0.22
Age	2	41.00	1.58	0.45	0.10	-18.49	0.33
Sex	2	41.07	1.65	0.44	0.10	-18.53	0.42
Date	2	41.17	1.75	0.42	0.09	-18.58	0.52
Imp1.859	2	41.43	2.01	0.37	0.08	-18.71	0.60
Lon	2	41.45	2.03	0.36	0.08	-18.72	0.68
Imp3.900	2	41.53	2.11	0.35	0.08	-18.76	0.76
Lat	2	42.08	2.65	0.27	0.06	-19.03	0.82
Age + Sex	3	42.81	3.39	0.18	0.04	-18.39	0.86
Age* Sex	4	44.82	5.40	0.07	0.02	-18.38	0.87
Imp1.859*Age	4	44.84	5.41	0.07	0.01	-18.39	0.89
Imp3.900*Age	4	45.07	5.65	0.06	0.01	-18.51	0.90
Imp1.859*Date	4	45.08	5.66	0.06	0.01	-18.51	0.91
Imp3.900*Date	4	45.19	5.77	0.06	0.01	-18.57	0.93
Imp1.859*Sex	4	45.22	5.80	0.06	0.01	-18.58	0.94
Imp3.900*Sex	4	45.27	5.85	0.05	0.01	-18.61	0.95
Imp3.900*Lon	4	45.34	5.91	0.05	0.01	-18.64	0.96
Imp1.859*Lon	4	45.34	5.92	0.05	0.01	-18.64	0.97
Imp3.900*Lat	4	45.78	6.36	0.04	0.01	-18.86	0.98
Imp1.859*Lat	4	45.88	6.45	0.04	0.01	-18.91	0.99
Year	6	47.55	8.13	0.02	0.00	-17.71	1.00
Year + Date	7	49.14	9.72	0.01	0.00	-17.49	1.00
BCR	7	49.38	9.96	0.01	0.00	-17.61	1.00
Imp1.859*Year	12	58.97	19.54	0.00	0.00	-17.25	1.00
Imp3.900*Year	12	59.10	19.68	0.00	0.00	-17.32	1.00
Imp3.900*BCR	14	63.99	24.56	0.00	0.00	-17.68	1.00
Imp1.859*BCR	14	64.14	24.72	0.00	0.00	-17.76	1.00

Supplementary Table 10. AICc results for generalized linear models predicting stop type (<1 day "stop" or >1 day "stopover) of the migratory stopping events of GPS-tagged American Woodcock migrating through eastern North America in the fall of 2017-2022. "Imp1.859" refers to mean percent impervious surface cover within 1.859 km of stopping event center, and "Imp3.900" refers to mean percent impervious surface cover within 3.900 km of stopping event center. "BCR" refers to bird conservation region. The null model is an intercept-only model.

	Model Name	K	AICc	ΔAICc	AICc Weight	Cumulative Weight	Log-Likelihood
Tier 1	**Null**	**1**	**17.47**	**0.00**	**0.48**	**0.48**	**-7.73**
	Age	2	18.81	1.35	0.24	0.72	-7.40
	Sex	2	19.62	2.15	0.16	0.89	-7.80
	Age + Sex	3	20.96	3.49	0.08	0.97	-7.46
	Age*Sex	4	22.99	5.52	0.03	1.00	-7.46
Tier 2	**Null**	**1**	**17.47**	**0.00**	**0.74**	**0.74**	**-7.73**
	Date	2	20.01	2.55	0.21	0.95	-8.00
	Year	4	23.32	5.85	0.04	0.99	-7.63
	Year + Date	5	25.91	8.44	0.01	1.00	-7.90
Tier 3	**Null**	**1**	**17.47**	**0.00**	**0.52**	**0.52**	**-7.73**
	Lat	2	19.32	1.86	0.20	0.72	-7.65
	Lon	2	19.43	1.97	0.19	0.92	-7.71
	Lat + Lon	3	21.10	3.63	0.08	1.00	-7.53
	BCR	9	31.22	13.76	0.00	1.00	-6.47

Supplementary Table 11. AICc selection process for linear models predicting the stop type (<1 day "stop" or >1 day "stopover) of the migratory stopping events of GPS tagged American Woodcock migrating through eastern North America in the spring between 2017 and 2022. A tiered model selection approach was used to establish the most supported combination of individual, spatial, and temporal variables, where the most supported model (lowest ΔAICc score) that also had an effect for all variables that was significant at an α of 0.05 was carried forward as an additive effect in the next tier. The models that were carried forward are shown in bold. The most supported model at tier three was used to account for confounding variables in tests of additive and interactive effects of impervious surface cover on stopping event type. "BCR" refers to bird conservation region. The null model is an intercept-only model.

Model Name	K	AICc	ΔAICc	Model Likelihood	AICc Weight	Log-Likelihood	Cumulative Weight
Age	3	3782.37	0.00	1.00	0.16	-1888.14	0.16
Age + Sex	4	3783.02	0.65	0.72	0.12	-1887.43	0.28
Null	2	3783.47	1.10	0.58	0.09	-1889.71	0.37
Sex	3	3784.31	1.94	0.38	0.06	-1889.11	0.43
Imp1.859	3	3784.36	1.99	0.37	0.06	-1889.14	0.49
Date	3	3784.42	2.05	0.36	0.06	-1889.17	0.55
Lat	3	3784.71	2.34	0.31	0.05	-1889.31	0.60
Imp3.900	3	3784.92	2.55	0.28	0.05	-1889.41	0.65
Imp3.900*Age	5	3784.95	2.58	0.28	0.04	-1887.36	0.69
Imp1.859*Age	5	3784.97	2.60	0.27	0.04	-1887.37	0.74
Age*Sex	5	3785.10	2.72	0.26	0.04	-1887.43	0.78
Lon	3	3785.45	3.08	0.21	0.03	-1889.68	0.81
BCR	8	3785.78	3.41	0.18	0.03	-1884.61	0.84
Imp1.859*Lat	5	3785.84	3.47	0.18	0.03	-1887.81	0.87
Imp3.900*Lat	5	3786.11	3.74	0.15	0.03	-1887.94	0.90
Lat + Lon	4	3786.21	3.84	0.15	0.02	-1889.03	0.92
Imp1.859*Sex	5	3787.08	4.71	0.09	0.02	-1888.42	0.94
Imp1.859*Date	5	3787.44	5.07	0.08	0.01	-1888.60	0.95
Imp3.900*Sex	5	3787.44	5.07	0.08	0.01	-1888.61	0.96
Imp3.900*Date	5	3787.79	5.42	0.07	0.01	-1888.78	0.97
Imp3.900*Lon	5	3788.02	5.65	0.06	0.01	-1888.89	0.98
Imp1.859*Lon	5	3788.15	5.78	0.06	0.01	-1888.96	0.99
Year	5	3789.33	6.96	0.03	0.01	-1889.55	1.00
Year + Date	6	3790.35	7.98	0.02	0.00	-1889.02	1.00
Imp1.859*Year	9	3795.72	13.35	0.00	0.00	-1888.51	1.00
Imp3.900*Year	9	3796.05	13.68	0.00	0.00	-1888.68	1.00

Imp1.859*BCR	15	3798.90	16.53	0.00	0.00	-1883.50	1.00
Imp3.900*BCR	15	3799.68	17.31	0.00	0.00	-1883.89	1.00

Supplementary Table 12. AICc results for generalized linear models predicting stop type (<1 day “stop” or >1 day “stopover) of the migratory stopping events of GPS-tagged American Woodcock migrating through eastern North America in the spring of 2017-2022. “Imp1.859” refers to mean percent impervious surface cover within 1.859 km of stopping event center, and “Imp3.900” refers to mean percent impervious surface cover within 3.900 km of stopping event center. “BCR” refers to bird conservation region. The null model is an intercept-only model.

	Model Name	K	AICc	ΔAICc	AICc Weight	Cumulative Weight	Log-Likelihood
Tier 1	**Null**	**2**	**7414.72**	**0.00**	**0.30**	**0.30**	**-3705.35**
	Sex	3	7415.24	0.51	0.23	0.53	-3704.59
	Age	3	7415.78	1.06	0.18	0.70	-3704.87
	Age*Sex	5	7415.82	1.10	0.17	0.87	-3702.85
	Age + Sex	4	7416.44	1.72	0.13	1.00	-3704.18
Tier 2	Year + Date	8	7405.23	0.00	0.63	0.63	-3694.48
	Year	7	7406.38	1.15	0.36	0.99	-3696.08
	Date	3	7413.88	8.65	0.01	0.99	-3703.92
	Null	**2**	**7414.72**	**9.49**	**0.01**	**1.00**	**-3705.35**
Tier 3	**Lat**	**3**	**7383.16**	**0.00**	**0.71**	**0.71**	**-3688.56**
	Lat + Lon	4	7384.96	1.80	0.29	1.00	-3688.44
	BCR	8	7394.82	11.65	0.00	1.00	-3689.27
	Lon	3	7403.61	20.44	0.00	1.00	-3698.78
	Null	2	7414.72	31.56	0.00	1.00	-3705.35

Supplementary Table 13. AICc selection process for linear models predicting the migratory step distance, in km, following the stopping events of GPS tagged American Woodcock migrating through eastern North America in the fall between 2017 and 2022. A tiered model selection approach was used to establish the most supported combination of individual, spatial, and temporal variables, where the most supported model (lowest ΔAICc score) that also had an effect for all variables that was significant at an α of 0.05 was carried forward as an additive effect in the next tier. The models that were carried forward are shown in bold. The most supported model at tier three was used to account for confounding variables in tests of additive and interactive effects of impervious surface cover on migratory step distance "BCR" refers to bird conservation region. The null model is an intercept-only model.

Model Name	K	AICc	ΔAICc	Model Likelihood	AICc Weight	Log-Likelihood	Cumulative Weight
Lat + Imp1.859	4	7382.46	0.00	1.00	0.20	-3687.19	0.20
Lat	3	7383.16	0.71	0.70	0.14	-3688.56	0.35
Lat + Imp3.900	4	7383.26	0.81	0.67	0.14	-3687.59	0.48
Lat + Imp1.859*Lat	5	7384.34	1.89	0.39	0.08	-3687.11	0.56
Lat + Lon	4	7384.96	2.51	0.29	0.06	-3688.44	0.62
Lat + Imp3.900*Lat	5	7385.28	2.82	0.24	0.05	-3687.58	0.67
Lat + Imp1.859*age	6	7385.44	2.99	0.22	0.05	-3686.64	0.71
Lat + Imp3.900*Date	6	7385.63	3.17	0.20	0.04	-3686.73	0.75
Lat + Imp1.859*Date	6	7385.69	3.23	0.20	0.04	-3686.76	0.79
Lat + Imp1.859*Year	14	7385.69	3.24	0.20	0.04	-3678.43	0.83
Lat + Imp1859*Sex	6	7385.92	3.46	0.18	0.04	-3686.88	0.87
Lat + Imp3.900*Age	6	7386.10	3.64	0.16	0.03	-3686.97	0.90
Lat + Imp1.859*Lon	6	7386.37	3.91	0.14	0.03	-3687.10	0.93
Lat + Imp3.900*Sex	6	7386.51	4.06	0.13	0.03	-3687.17	0.96
Lat + Imp3.900*Year	14	7386.85	4.39	0.11	0.02	-3679.01	0.98
Lat + Imp3.900*Lon	6	7387.22	4.76	0.09	0.02	-3687.53	1.00

BCR	8	7394.82	12.36	0.00	0.00	-3689.27	1.00
Lon	3	7403.61	21.15	0.00	0.00	-3698.78	1.00
Year + Date	8	7405.23	22.78	0.00	0.00	-3694.48	1.00
Imp3.900*BCR	15	7405.76	23.30	0.00	0.00	-3687.40	1.00
Year	7	7406.38	23.93	0.00	0.00	-3696.08	1.00
Imp1.859*BCR	15	7406.58	24.13	0.00	0.00	-3687.82	1.00
Date	3	7413.88	31.43	0.00	0.00	-3703.92	1.00
Null	2	7414.72	32.27	0.00	0.00	-3705.35	1.00
Sex	3	7415.24	32.78	0.00	0.00	-3704.59	1.00
Age	3	7415.78	33.32	0.00	0.00	-3704.87	1.00
Imp1.859	3	7415.81	33.35	0.00	0.00	-3704.88	1.00
Age*Sex	5	7415.82	33.37	0.00	0.00	-3702.85	1.00
Imp3.900	3	7416.32	33.86	0.00	0.00	-3705.14	1.00
Age + Sex	4	7416.44	33.98	0.00	0.00	-3704.18	1.00

Supplementary Table 14. AICc results for generalized linear models predicting migratory step distance, in km, following the stopping events of GPS-tagged American Woodcock migrating through eastern North America in the fall of 2017-2022. “Imp1.859” refers to mean percent impervious surface cover within 1.859 km of stopping event center, and “Imp3.900” refers to mean percent impervious surface cover within 3.900 km of stopping event center. “BCR” refers to bird conservation region. The null model is an intercept-only model.

	Model Name	K	AICc	ΔAICc	AICc Weight	Cumulative Weight	Log-Likelihood
Tier 1	Sex	3	6810.72	0.00	0.31	0.31	-3402.33
	Age*Sex	**5**	**6810.95**	**0.24**	**0.27**	**0.58**	**-3400.42**
	Age + Sex	4	6811.73	1.01	0.19	0.77	-3401.82
	Null	2	6812.12	1.40	0.15	0.92	-3404.05
	Age	3	6813.36	2.64	0.08	1.00	-3403.66
Tier 2	Year + Date	6	6794.97	0.00	0.75	0.75	-3391.40
	Age*Sex + Date	**6**	**6797.17**	**2.21**	**0.25**	**1.00**	**-3392.50**
	Year	5	6807.92	12.96	0.00	1.00	-3398.90
	Age*Sex	5	6810.95	15.99	0.00	1.00	-3400.42
Tier 3	Age*Sex + Date + Lat + Lon	8	6716.83	0.00	0.67	0.67	-3350.27
	Age*Sex + Date + Lat	**7**	**6718.29**	**1.46**	**0.32**	**1.00**	**-3352.03**
	Date + BCR	11	6736.93	20.10	0.00	1.00	-3357.19
	Age*Sex + Date + Lon	7	6795.34	78.51	0.00	1.00	-3390.56
	Age*Sex + Date	6	6797.17	80.34	0.00	1.00	-3392.50

Supplementary Table 15. AICc selection process for linear models predicting the migratory step distance, in km, following the stopping events of GPS tagged American Woodcock migrating through eastern North America in the spring between 2017 and 2022. A tiered model selection approach was used to establish the most supported combination of individual, spatial, and temporal variables, where the most supported model (lowest ΔAICc score) that also had an effect for all variables that was significant at an α of 0.05 was carried forward as an additive effect in the next tier. The models that were carried forward are shown in bold. The most supported model at tier three was used to account for confounding variables in tests of additive and interactive effects of impervious surface cover on migratory step distance "BCR" refers to bird conservation region. The null model is an intercept-only model.

Model Name	**K**	**AICc**	**ΔAICc**	**Model Likelihood**	**AICc Weight**	**Log-Likelihood**	**Cumulative Weight**
Age*Sex + Date + Lat + Lon	8	6716.83	0.00	1.00	0.26	-3350.27	0.26
Age*Sex + Date + Lat	7	6718.29	1.46	0.48	0.13	-3352.03	0.39
Age*Sex + Date + Lat + Imp3.900*Lon	10	6718.76	1.93	0.38	0.10	-3349.16	0.49
Age*Sex + Date + Lat + Imp1.859*Lon	10	6719.20	2.37	0.31	0.08	-3349.37	0.57
Age*Sex + Date + Lat + Imp3.900*Sex	9	6719.28	2.45	0.29	0.08	-3350.45	0.65
Age*Sex + Date + Lat + Imp3.900	8	6719.88	3.06	0.22	0.06	-3351.80	0.71
Age*Sex + Date + Lat + Imp1.859	8	6719.98	3.15	0.21	0.05	-3351.84	0.76
Age*Sex + Date + Lat + Imp3.900*Lat	9	6720.15	3.32	0.19	0.05	-3350.89	0.81
Age*Sex + Date + Lat + Imp1.859*Sex	9	6720.53	3.70	0.16	0.04	-3351.08	0.86
Age*Sex + Date + Lat + Imp1.859*Lat	9	6721.71	4.88	0.09	0.02	-3351.67	0.88
Age*Sex + Date + Lat + Imp1.859*Age	9	6721.81	4.98	0.08	0.02	-3351.72	0.90
Date + Lat + Imp1.859*Year	11	6721.81	4.98	0.08	0.02	-3349.63	0.92

Age*Sex + Date + Lat + Imp1.859*Date	9	6721.90	5.07	0.08	0.02	-3351.76	0.94
Age*Sex + Date + Lat + Imp3.900*Age	9	6721.94	5.11	0.08	0.02	-3351.79	0.96
Age*Sex + Date + Lat + Imp3.900*Date	9	6721.94	5.11	0.08	0.02	-3351.79	0.98
Date + Lat + Imp3.900*Year	11	6722.55	5.72	0.06	0.02	-3350.00	1.00
Date + BCR	11	6736.93	20.10	0.00	0.00	-3357.19	1.00
Date + Imp1.859*BCR	19	6741.84	25.01	0.00	0.00	-3351.13	1.00
Date + Imp3.900*BCR	19	6742.45	25.62	0.00	0.00	-3351.43	1.00
Year + Date	6	6794.97	78.14	0.00	0.00	-3391.40	1.00
Age*Sex + Date + Lon	7	6795.34	78.51	0.00	0.00	-3390.56	1.00
Age*Sex + date	6	6797.17	80.34	0.00	0.00	-3392.50	1.00
Year	5	6807.92	91.09	0.00	0.00	-3398.90	1.00
Sex	3	6810.72	93.89	0.00	0.00	-3402.33	1.00
Age*Sex	5	6810.95	94.12	0.00	0.00	-3400.42	1.00
Age + Sex	4	6811.73	94.90	0.00	0.00	-3401.82	1.00
Null	2	6812.12	95.29	0.00	0.00	-3404.05	1.00
Age	3	6813.36	96.53	0.00	0.00	-3403.66	1.00

Imp1.859	3	6813.96	97.13	0.00	0.00	-3403.96	1.00
Imp3.900	3	6814.07	97.24	0.00	0.00	-3404.01	1.00

Supplementary Table 16. AICc results for generalized linear models predicting migratory step distance, in km, following the stopping events of GPS-tagged American Woodcock migrating through eastern North America in the spring of 2017-2022. "Imp1.859" refers to mean percent impervious surface cover within 1.859 km of stopping event center, and "Imp3.900" refers to mean percent impervious surface cover within 3.900 km of stopping event center. "BCR" refers to bird conservation region. The null model is an intercept-only model.

AUTHOR'S BIOGRAPHY

Zoe Pavlik is from Durham, New Hampshire. She double majored in Ecology and Environmental Sciences and Wildlife Ecology at the University of Maine. Her hobbies include running, board games, and playing the cello and the flute. While in college, she participated in a variety of musical groups including UMaine orchestra, marching band, and a smaller chamber ensemble. After college, she hopes to spend a few years getting more field research experience and figuring out whether she wants to go to grad school.