Ecological Informatics 70 (2022) 101701

Contents lists available at ScienceDirect

Ecological Informatics

journal homepage: www.elsevier.com/locate/ecolinf

Assessment of appropriate species-specific time intervals to integrate GPS telemetry data in ecological niche models

Jason V. Lombardi [a,*], Humberto L. Perotto-Baldivieso [a], David G. Hewitt [a], Daniel G. Scognamillo [a], Tyler A. Campbell [b], Michael E. Tewes [a]

[a] Caesar Kleberg Wildlife Research Institute, Texas A&M University-Kingsville, 700 University Boulevard MSC 218, Kingsville, TX 78363, USA
[b] East Foundation, 200 Concord Plaza Drive #410, San Antonio, TX 78216, USA

ARTICLE INFO

Keywords:
Ecological niche models
MaxEnt
Leopardus pardalis
Omission rates
Ocelot
Serial autocorrelation

ABSTRACT

Ecological niche models use presence-only data, which is often affected by lack of true absences leading to sampling bias. Over the last decade, there has been an uptick in the integration of occurrence data from global positioning systems telemetry data in ecological niche models and/or species distribution models. These data types can be affected by serial autocorrelation at high relocation frequencies yet have been used in ecological niche models using geographic filters and subsampling techniques. Yet, no study to date has attempted to discern a method to identify the appropriate time interval for a particular species if integrating GPS telemetry occurrence data in a MaxEnt framework. We demonstrate a rigorous spatial technique using a robust contemporary dataset from ocelots (*Leopardus pardalis*) to assess the appropriate time intervals to use in a species-specific ecological niche model. We assessed a range of daily time intervals (every 0.5, 1–4, 6, 8, and 12 h) commonly used in teresstrial mammalian carnivore studies. We observed the predictive performance of shorter time intervals every 2 h was comparable to much longer intervals every 12 h. These shorter intervals under/overestimated the least amount of data compared to 12 h. This study demonstrates that by accounting for serial autocorrelation and conducting rigorous spatial analyses, scientists can identify the appropriate time interval to integrate GPS telemetry data use in ecological niche models in MaxEnt. These results can also be transferable across highly mobile terrestrial taxa at different spatial scales, which can help inform species management or conservation strategies.

1. Introduction

Over the last 60 years, wildlife ecologists have used telemetry to understand the study of animal movement, space use, and resource utilization for a wide range of species globally (Milspaugh et al., 2012, Hofman et al., 2019). Initially, animal movement data was constrained by the use of very high frequency (VHF) radio collars that prevented continuous data collection through space and time (Kays et al., 2015). More recently since the late 1990s, these tracking devices and collars have now advanced with the use of Global Positioning System (GPS), which increases temporal resolution and spatial accuracy (Hebblewhite and Haydon, 2010, Kays et al., 2015, Hofman et al., 2019). This increase in temporal resolution and spatial accuracy has allowed scientists to gain a stronger understanding of wildlife behavior such as movement patterns and home range distributions across urban and remote landscapes (Hebblewhite and Haydon, 2010, Milspaugh et al. 2012, Kays et al., 2015).

Such large datasets derived from current GPS and satellite collars have allowed researchers to develop rigorous statistical approaches due to the ability to connect sequential successive locations at fine time intervals (Lombardi et al., 2021; Perotto-Baldivieso et al., 2012; Ward, 2016). However, these repeated steps can be inherently nonindependent or autocorrelated, which violates assumptions related to estimating animal space use and distributions (Cagnacci et al., 2010; De Solla et al., 1999; Dormann, 2007; Kays et al., 2015; Perotto-Baldivieso et al., 2012), with a higher frequency of locations having a stronger correlation (Boyce et al., 2022; Cagnacci et al., 2010). Most studies attempt to eliminate or reduce autocorrelation from telemetry datasets by defining

Abbreviations: GPS, Global positioning systems; SDM, Species distribution models; ENM, Ecological niche models.

* Corresponding author.
E-mail addresses: lombardijv@gmail.com (J.V. Lombardi), humberto.perotto@tamuk.edu (H.L. Perotto-Baldivieso), david.hewitt@tamuk.edu (D.G. Hewitt), daniel.scognamillo@tamuk.edu (D.G. Scognamillo), tcampbell@eastfoundation.net (T.A. Campbell), michael.tewes@tamuk.edu (M.E. Tewes).

https://doi.org/10.1016/j.ecoinf.2022.101701
Received 16 February 2022; Received in revised form 25 May 2022; Accepted 30 May 2022
Available online 3 June 2022

a less frequent tracking schedule (Caso, 2013; Heard et al., 2008; Joly et al., 2015; Leonard et al., 2020; Thalmann et al., 2016) or subsampling (Beumer et al., 2019; De Solla et al., 1999; Lombardi et al., 2021; Poor et al., 2020), but often do not report the level of correlation.

Ecological niche modeling (ENM) is typically used by researchers with passive or non-invasive sampling such as camera-trap data, confirmed observations, harvest records, and natural history collections (Anderson and González, 2011; Duscher and Nopp-Mayr, 2017; Phillips et al., 2009). Ecological niche models contain environmental conditions under which species can maintain populations, and that model can then be transferred to different landscapes to predict distributional potential for the species (Elith et al., 2011). These models rely on the uniform sampling premise, which stipulates that data be sampled randomly across a landscape without autocorrelation between presence locations (Merow et al., 2013; Phillips et al., 2009). If biases or autocorrelation are suspected to exist in such sampling data, it has been suggested to use a bias file, which represents the relative sampling effort, spatial filter, or other statistical approaches (Crase et al., 2012; Kramer-Schadt et al., 2013; Václavík et al., 2012). Further, it has been suggested higher levels of autocorrelation could artificially inflate levels of model performance in ENMs (De Solla et al., 1999). Spatial autocorrelation, an extension of serial autocorrelation, is a pressing challenge when modeling ENMs, as left unchecked can lead to flawed analyses and violate assumptions of spatial independence Lichstein et al., 2002). Further, presence of spatial autocorrelation can artificially inflate the statistical significance of species-covariate relationships in ENMs (Dormann, 2007; Václavík et al., 2012).

Due to spatial autocorrelation issues, telemetry data have not been extensively used in ENMs as data are assumed biased (Fourcade et al., 2014). Although, over the last seven years, there has been an uptick in the number of studies that have integrated telemetry data into ecological niche models (Beumer et al., 2019; Chibeya et al., 2021; Coxen et al., 2017; Dempsey et al., 2015; Poor et al., 2020). Integration into these models has used various approaches to reduce temporal dependence and serial autocorrelation between locations. Spatial or geographic filters have been used in combination with taxa-specific behavioral subsampling in migratory birds (Coxen et al., 2017) and subsampling every 3 to 12 h for kit foxes (*Vulpes macrotis;* Dempsey et al., 2015) and musk oxen (*Ovibos moschatus*; Beumer et al., 2019). Chibeya et al. (2021) randomly filtered points and fixed a minimum 500 m distance between GPS relocation points to reduce serial autocorrelation for African elephants (*Loxodonta africana*). Behavioral filters (i.e., removal of transient individuals) combined with assumptions in independent temporal filters have also been used to reduce serial autocorrelation in MaxEnt and MaxLike frameworks (Poor et al., 2020). However, while these studies have taken suitable measures to attempt to reduce serial autocorrelation, to date, no study has reported the level of serial autocorrelation in these GPS data sources used in their studies.

Consideration for appropriate GPS telemetry time intervals has been shown to provide a meaningful benefit for assessing animal movements and distributions (Lombardi et al., 2021; Perotto-Baldivieso et al., 2012; Ward, 2016). We conducted the present study to demonstrate a new technique to assess whether different time intervals commonly used in GPS telemetry studies are appropriate to use in ecological niche models within a MaxEnt framework. To inform this study, we conducted an exploratory analysis using a robust contemporary ocelot (*Leopardus. pardalis*) GPS telemetry dataset and a small subset of sample environmental variables. To achieve this, we evaluated the optimal GPS time interval to inform this exploratory ENM analysis and assess its application for other taxa in future studies. Our objectives were to (1) Estimate the amount of serial autocorrelation between successful GPS telemetry locations (0.5–12 h) to determine an appropriate time interval to inform an ENM; (2) Evaluate the predictive performance of ENM created using different GPS time intervals (0.5–12 h); and (3) Determine the difference in the spatial distribution of predicted presence and ENM performance (i.e., over/underestimation) compared to a baseline model.

2. Materials and methods

2.1. Study system

This case study focused on the mosaic of >250,000 acres of private lands and cropland in northeastern Willacy County and eastern Kenedy County (Fig. 1), specifically located on the confluence of the Coastal Sand Plain, Lower Rio Grande Valley, and Laguna Madre Barrier Islands and Coastal Marshes eco-regions, Texas (Leonard et al., 2020; Lombardi et al., 2021). The fieldwork portion of the case study occurred on the East Foundation's El Sauz Ranch (113 km^2) in southeastern Kenedy and northeastern Willacy counties, Texas, USA. The surrounding mosaic of private lands was composed of active cropland, cattle ranches, low-fence hunting operations, and the small towns of San Perlita and Port Mansfield. The regional climate was semi-arid and subtropical (10^o C–36^o C), with highly erratic rainfall and episodic drought (Norwine and Kuruvilla, 2007). Natural features across this area include parabolic inland dunes, palustrine and coastal wetlands, irrigation canals, coastal prairie, grasslands, and large patches of dense woody vegetation communities (Leonard et al., 2020, Lombardi et al., 2021).

2.2. Telemetry data collection

We used a contemporary telemetry dataset from previous studies on collared adult ocelots ($n = 8$; 4 males; 4 females, Table 1) collected from January 2014 to July 2017 (Leonard et al., 2020; Lombardi et al., 2021; Veals et al., 2022). We did not capture live animals for this study, please see Leonard et al. (2020) and Lombardi et al. (2021) for specific details on capture and handling protocols used. Data were collected using Lotek Minitrack and Litetrack global positioning systems (GPS) and Iridium satellite-GPS collars that used a variety of time-interval schedules based on prior project objectives (i.e., every 30 min to every 12 h). The temporal extent of GPS data lasted on average 141 days (range 70–280 days) and occurred during all seasons throughout the year.

2.3. Temporal spatial autocorrelation analysis

For each GPS dataset, we first removed outlier geographic points that may have been a result of pre-deployment testing and locations collected within 24 h of capture to minimize bias due to live capture (Beumer et al., 2019; Lombardi et al., 2021). We applied a geographic filter to exclude locations that had a dilution of precision >10 (D'Eon and Delparte, 2005), less than four satellite coverage, and removed geographic outlier locations that may have been the result of an error (Lombardi et al., 2021).

To understand the effect of time intervals commonly used in mammalian studies on resultant ENMs, we assessed for serial autocorrelation of successive locations at different time intervals (Lombardi et al., 2021; Perotto-Baldivieso et al., 2012; Ward, 2016). We subsampled the data in ArcGIS 10.6.1 (ESRI, Redlands, California) at half hour, 1, 2, 3, 4, 5, 6, 8, and 12 h, which includes the raw location data that were collected at half hour and 12-h. Intervals were chosen based on a 24-h time cycle in a given day to ensure fixed times of each interval dataset and to compare to commonly used time intervals across mammalian studies (Benson et al., 2021; Lehnen et al., 2021; Leonard et al., 2020; Walton et al., 2018; Young et al., 2019). For each partitioned dataset, we calculated the Euclidean distance (m) between two successive locations (Lombardi et al., 2021). We used Pearson's correlation analysis (significance $P = 0.05$) to determine the similarity between pairs of successive steps. We postulated that shorter time intervals (i.e., 30 min) will have the highest serial positive correlation, and longer time intervals (i.e., 12 h) would have minimal serial autocorrelation and not be positively correlated.

Serial autocorrelations among successive telemetry locations will decline at longer time intervals such that those are likely most independent. Twelve hour time intervals have previously been used in

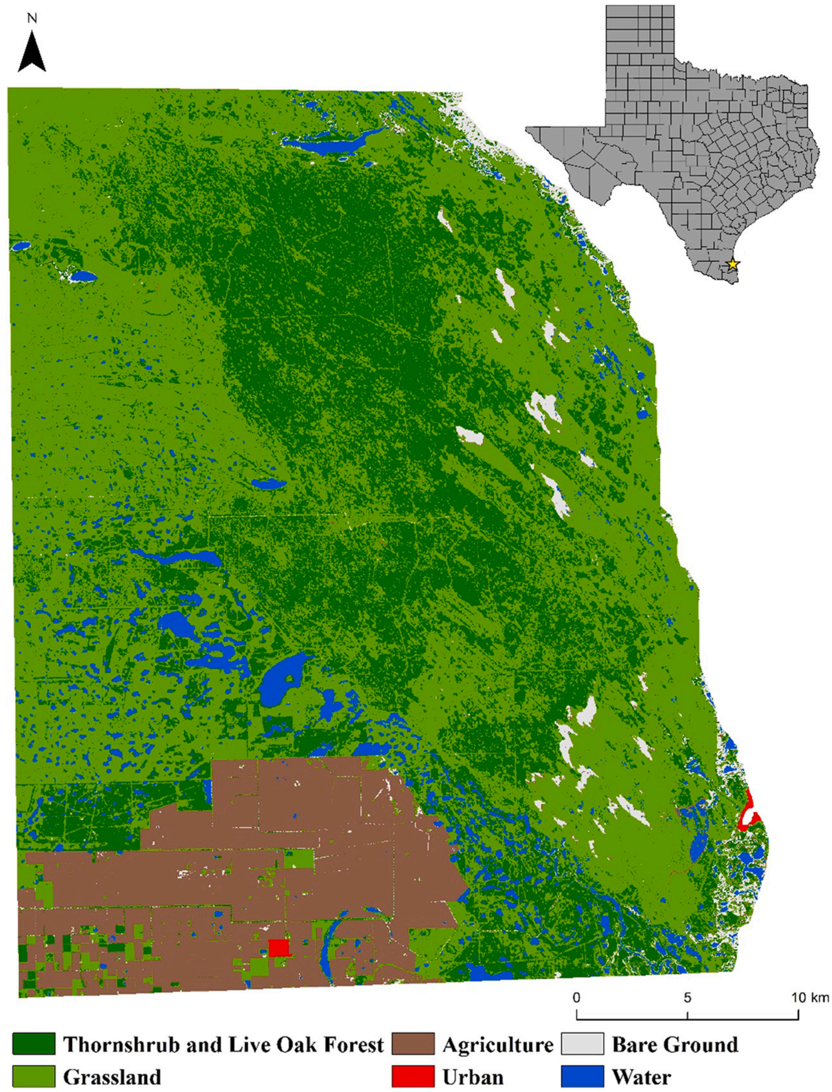

Fig. 1. Location of ranchland study system used in this analysis in southern Texas.

Table 1
Summary table of individual adult ocelot GPS dataset (total locations, and partitioned time intervals (0.5, 1, 2, 3, 4, 6, 8, and 12 h) used in this exploratory analysis. Data were collected in eastern Kenedy and northeastern Willacy counties, Texas, USA from March 2014 to May 2017.

ID[1]	Begin	End	Total	0.5	1	2	3	4	6	8	12
O17F	25 Jan 17	17 May 17	2951	2841	1480	704	475	416	236	179	119
O5M	16 Jan 17	27 Mar 17	1308	1171	646	323	250	163	110	85	57
O6M	20 Apr 15	25 Jan 16	1408	747	569	344	515	414	244	379	135
O12F	20 Mar-15	29 Sep 15	545	436	183	134	65	146	126	106	105
O12M	16 Mar 14	9 Sep 14	630	525	391	297	237	206	197	110	176
O10F	1 Mar 14	13 Jul 14	506	333	201	129	95	81	68	67	56
O14F	22 Apr 16	20 Sep 16	588	269	175	95	77	64	64	36	45
O15M[2]	14 Jan 17	1 Feb 17	338	220	124	61	39	31	14	16	10
Total			8274	6542	3769	2087	1753	1521	1059	978	703

[1] ID refers to individual ocelot (O) ID ("M" or "F" refers to male or female).

studies on neotropical felids (Caso, 2013; Leonard et al., 2020), Tasmanian devils (Thalmann et al., 2016), and larger ungulates (Heard et al., 2008; Joly et al., 2015; Perotto-Baldivieso et al., 2012); therefore, we used this time interval as an appropriate baseline dataset in deriving ENMs for this study. ENMs. However, GPS time intervals recorded at higher frequencies (i.e., every half-hour) often violate assumptions of independence that are required by many models, requiring the use of correlation matrices to account for the correlated structure of these datasets (Dray et al., 2010; Perotto-Baldivieso et al., 2012).

2.4. Exploratory ecological niche modeling

For this exploratory ENM analysis to assess the predictive performance at different time intervals, we used a subset of three environmental variables related to ocelot ecology in the region (Harveson et al., 2004, Gómez-Ramírez et al., 2017, Lombardi et al., 2021). We acknowledge that more variables are likely to influence a species-specific ENM, but the goal of this analysis was not to estimate suitable habitat or variables likely to influence ocelots, we aimed to assess whether different time intervals of the dataset affected model performance and spatial distribution of occurrence data. We fit a single set of environmental variables ($n = 3$) for comparison purposes. We did not include annual bioclimatic variables in this study due to the small geographic spatial extent of the dataset within this study system.

We conducted an unsupervised land cover classification for the entire ranchland study system using 30 m LANDSAT 8 imagery from 2016 in ERDAS IMAGINE (Hexagon Geospatial, Norcross, GA, USA). Following methodologies defined by Lombardi et al. (2021), we classified land-use types in the region into six broad land cover categories: agriculture (row-crop agriculture), bare ground (e.g., inland dunes, beaches), herbaceous cover (e.g., tall-mid prairie, and cordgrass (*Spartina* spp.) pasture), urban (towns and village), water (canals, lagunas, and wetlands), and woody vegetation (live oak forest and thornshrub forest). We manually digitized urban areas and mosaicked the layer into the raster following an accuracy assessment (i.e., 85% threshold) using 200 random points. We included a 30 m one arc-second digital elevation model (DEM) obtained from the US Geological Survey as ocelots have been documented at varying elevations across their range (Gómez-Ramírez et al., 2017; Harveson et al., 2004). Due to the association between canopy cover and ocelot habitat use (Harveson et al., 2004); we used the 2016 US Geological Survey Canopy Cover 30 m rasters as an index of canopy cover. Variables were resampled at 30 × 30 m resolution and screened for correlation.

We compared each time interval dataset using an ENM within MaxEnt (Version 3.3.1; Phillips et al., 2006). We performed 10 bootstrap replicates in which we randomly selected 75% of the locations to train the model, with the remaining 25% left to evaluate the model. Each bootstrap replicates used 10,000 background points sampled from the study area (Kramer-Schadt et al., 2013). Due to the exploratory nature of the study and because fit a small set of three covariates, we only fit one global model per time interval dataset (each with their occurrence sample size) which precluded our ability to run a model selection process for each time interval. To assess the predictive performance (model quality) of each time interval model, we compared omission rates for each time interval model, covariate contributions, and conducted a spatial assessment of each model. We evaluated the training and testing omission rates for minimum training presence and 10% training presence values (Cuyckens et al., 2015; Radosavljevic and Anderson, 2014). The minimum training presence indicated the least suitable environmental characteristics for which a locality was available in the training data and the 10% training presence is a value that excludes 10% of the areas with the lowest predicted values (Radosavljevic and Anderson, 2014). We also evaluated the sensitivity plus specificity threshold for each model, which maximizes correctly predicted absences (sum of the specificity) and correctly predicted presences (sum of the sensitivity) (Cuyckens et al., 2015).

2.5. Spatial assessment of time intervals in ecological niche models

We conducted spatial analyses in ArcMap 10.6.1 (ESRI, Redlands, CA, USA) to determine the difference in the spatial distribution of areas identified as suitable habitat or “probability of presence” by the models and differences in model performance for each temporal dataset compared to our baseline 12 h model. We compared models on a pixel-by-pixel basis of presence probabilities using a raster calculator in ArcMap 10.6.1 and reclassified each resulting raster map based on five percentile breaks (−0.10, −0.05, 0, 0.05, and 0.10). We quantified the proportion of area and predicted presence values in each model under or overestimated by 10% (< -0.10 and > 0.10) compared to our 12 h model. For the 12 h model, we used the minimum training presence criterion, to identify the minimum area that contained presence data (Cruz et al., 2019). We used the maximum training sensitivity plus specificity threshold (0.285) to identify the breakpoint for 10% under- and over-estimation used to compare against the baseline (Cruz et al., 2019).

3. Results

We observed a significant positive correlation among successive locations for the half-hour time interval, as expected, and observed no significant positive correlation for the other time intervals (Fig. 2). We observed a large drop in the serial correlation between half-hour and one hour, between one hour and 12 h had a similar correlation near zero (Fig. 2). Omission rates for each model were close to the predicted omission rates and each had low minimum training presence omission rates (Fig. 3). Two-hour time intervals had the lowest training and test omission rates for maximum sensitivity plus specificity thresholds among models considered and were closest to our baseline 12-h model (Table 2). Contributions of each variable slightly differed across time interval models (Fig. 4), but we will not explore these further because it was beyond the scope of our study.

Half-hour data and eight-hour data had the greatest percentage of presence probabilities that were underestimated compared to the 12 h model (Fig. 5). Based on the 10% threshold, each dataset underestimated <10% of the total estimated ocelot presence probability (Table 3). Two hour time intervals produced the lowest difference (<2.5%) in under- and overestimation of estimated ocelot presence (Fig. 5). We observed a similar difference in proportion (<2.5%) of under/overestimation based on three hour intervals, but this interval slightly underestimated more data beyond the criterion threshold (Fig. 4). Four to eight hour time intervals over/underestimated the greatest proportion of areas of ocelot presence and half hour and eight hour time intervals overestimated the greatest proportions of presence probability beyond the criterion threshold (Fig. 5).

4. Discussion

This study shows the importance of carefully selecting proper time intervals to reduce serial autocorrelation if integrating high-frequency GPS telemetry data in a MaxEnt framework for ecological niche modeling. Over the last 15 years, a growing body of knowledge and extensions of ecological niche modeling has been built on MaxEnt (Phillips et al., 2009, Anderson and González, 2011, Elith et al., 2011, Merow et al., 2013, Kramer-Schadt et al., 2013, Yackulic et al., 2013). At the same time, advances in telemetry technology have led to an explosion of data on animal movement and distribution, which has contributed to the field of movement ecology (Baasch et al., 2010) and forays into species distribution modeling (Edren et al. 2010, Limiñana et al., 2015, Dempsey et al., 2015, Chibeya et al., 2021, Poor et al., 2020). As of January 2020, Movebank (Wikelski et al., 2020), an online data repository for animal movement data has grown to >2.4 billion locations across 989 taxa from >7600 studies worldwide. Because the higher level of autocorrelation found in higher frequency GPS telemetry datasets (e.g., 5, 10, 15, and 30-min intervals) can inflate model performance and impact the ability to discern space use and distribution estimates, our study supports the notion of accounting for spatial autocorrelation, analyze, compare and identify the optimal time interval telemetry datasets to use MaxEnt framework. Future development of MaxEnt or species distribution modeling R-packages such as megaSDM (Shipley et al., 2022) and dismo (Hijmans et al., 2017) could include serial correlation factors or autocorrelograms to allow scientists to integrate GPS data and avoid sampling biases. This has important implications for the use of GPS telemetry in such models, as researchers will be able to understand the differences in time intervals that may affect model performance differently.

For ocelots, as with other territorial wide-ranging carnivores, longer time intervals can create uncertainty in animal activity and may obscure key information regarding behavior and fine-scale resource use (Perotto-

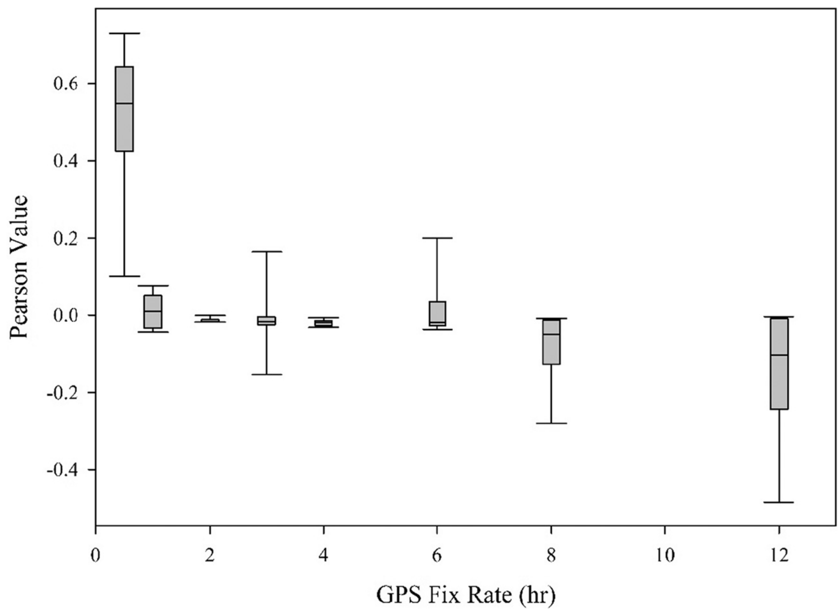

Fig. 2. Mean Pearson correlation coefficients for GPS time intervals: 0.5 h (n = 6542 locations), 1 h (n = 3769 locations), 2 h (n = 2087 locations), 3 h (n = 1753 locations), 4 h (n = 1521 locations), 6 h (n = 1059 locations), 8 h (n = 978 locations), and 12 h (n = 703 locations) used in this analysis.

Baldivieso et al., 2012; Schwager et al., 2007). Our case study shows promise and indicates GPS data from telemetered ocelots can be used to inform a potential ENM for ocelots. To retain biologically meaningful inferences and data independence for estimating ENMs, two hour time intervals were comparable to 12 h time intervals. Two hour intervals under- and overestimated the least amount of data compared to 12 h intervals. Further, two-hour intervals had among the lowest omission rates especially the testing maximum sensitivity plus specificity thresholds, which was the lowest among all intervals. These shorter intervals may represent the optimal interval for researchers attempting to gain as much GPS data while avoiding serial autocorrelation at higher frequencies. While two-hour time intervals may be considered high frequency, successive locations were not highly positively correlated ($p = 0.002$) between successive GPS locations. Knowledge of the exact time interval needed to collect biologically meaningful data can vary across species, depending on distribution, space use, age, and behavior (Lombardi et al., 2021; Perotto-Baldivieso et al., 2012; Ward, 2016). We recommend studies follow this spatial analytical approach to ensure they identify the optimal interval to answer their research question (Perotto-Baldivieso et al., 2012; Reynolds and Laundre, 1990; Swihart and Slade, 1985).

As we observed in this case study with ocelots, two and 12 h datasets had comparable model performance, but we would recommend using two-hour data to maximize the variability of potential environmental variables used throughout the day for future analyses for ocelots. We are not discouraging using longer time intervals, but that will depend on study-specific hypotheses for a given species. Our original approach to assessing time intervals of GPS data in MaxEnt frameworks allows researchers plenty of opportunities to integrate these results into other movement ecology techniques (i.e., step- or resource- selection) as additional analyses and not function as a replacement. This allows researchers to gain a stronger understanding of the ecological processes that govern the roles different taxa may play in their environment. Although we did not perform a model selection in this study, based on the varied omission rates for training and testing data, model covariate contributions, and different spatial distribution of occurrence points we posit different time intervals will likely result in varied model selection results.

Uniform sampling is a key assumption when using MaxEnt, in which environmental conditions must be sampled in proportion to their availability regardless of their spatial pattern (Phillips et al., 2009). Most studies that use MaxEnt use presence-only data from camera trap studies, natural history collections, or harvest records (Cruz et al., 2019; Cuyckens et al., 2015; Duscher and Nopp-Mayr, 2017). Presence-only data collection can be affected by imperfect sampling and detection probabilities, due to the lack of true-absence data to designate which sites were searched (Coxen et al., 2017; Merow et al., 2013). It is assumed that if sampling is biased, one cannot differentiate if species locations receive the largest search effort or if certain locations are preferred (MacKenzie et al., 2017; Merow et al., 2013; Phillips et al., 2009). Unlike non-invasive surveys or observational obtained data, telemetry data allows substantively more occurrence data to be considered in a given area. These locations will be indicative of the locations that are preferred by the species (biologically and ecologically) and would represent true areas of occurrence or absence (either there or not) on the landscape. If similar environmental variables are present in areas where the target or collared animal did not visit, researchers can infer based on the ecology that the animal is likely to occur there (MacKenzie et al., 2017).

This study applies to telemetry datasets used in ENMs across taxa. Previous studies show telemetry data can be used in ENMs (Beumer et al., 2019; Chibeya et al., 2021; Coxen et al., 2017; Dempsey et al., 2015; Poor et al., 2020), and now we demonstrate a methodological process researchers can use to optimize their data partitioning for their desired research question. As a rule, we recommend researchers define potential temporal periods based on ecological information about the species and the scientific questions related to ENMs that are asked of the data, but these will differ from species to species. This has implications for the use of GPS telemetry, as researchers will be able to understand ecological processes that govern landscape patterns and ecological niches for different taxa such as carnivores, ungulates, and birds at regional and continental scales.

5. Conclusions

Our study represents an effort to assess an appropriate taxa-specific time interval to integrate GPS telemetry data into a MaxEnt framework by accounting for serial autocorrelation and rigorous spatial approaches. In our example, shorter time intervals might be a preferred tradeoff to longer 12-h intervals, which can allow researchers to increase variability

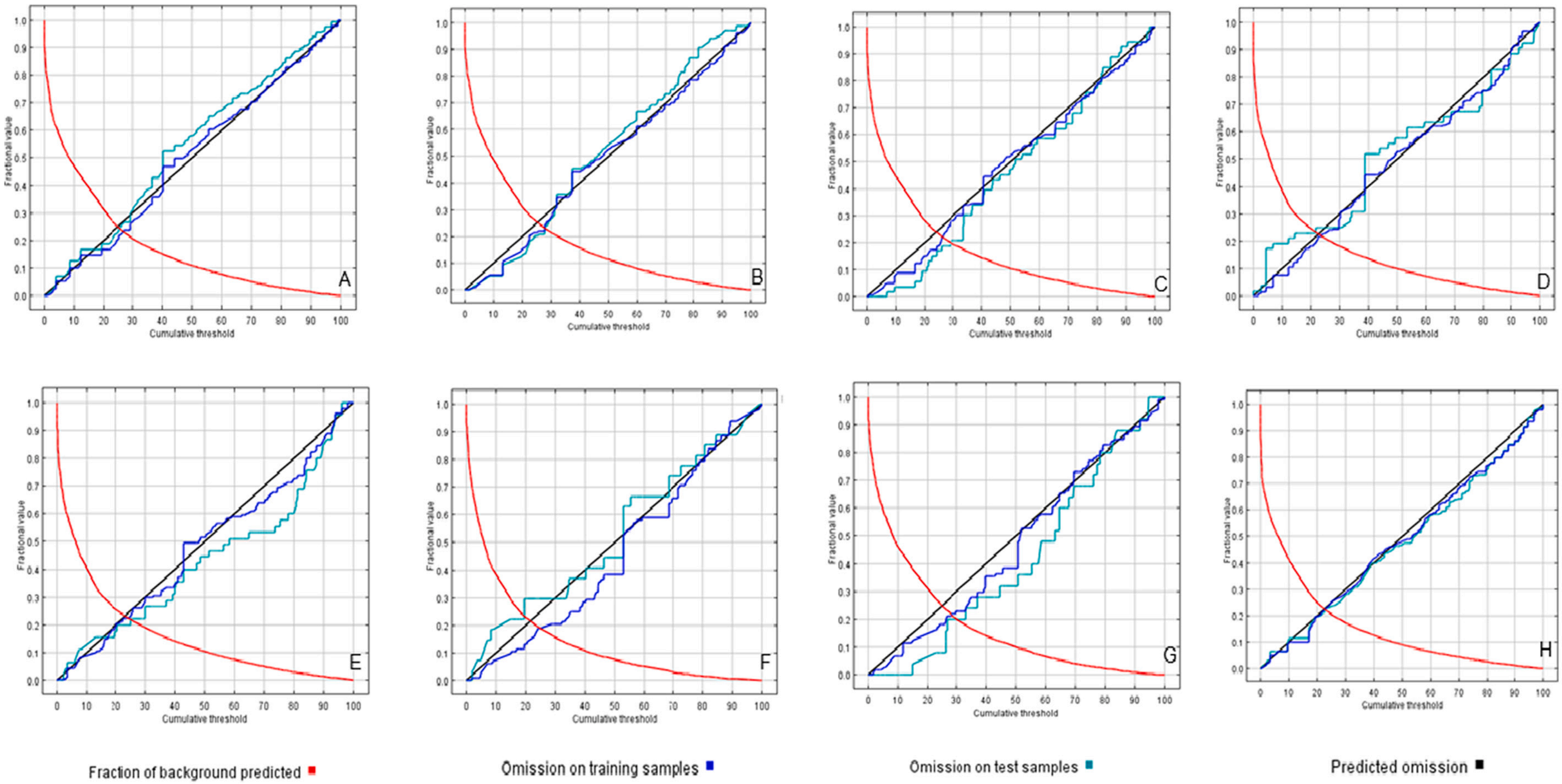

Fig. 3. Omission rate and predicted area as a function of the cumulative threshold for each time interval model (30 min [A], 1 h [B], 2 h [C], 3 h [D], 4 h [E], 6 h [F], 8 h [G], and 12 h [H]) considered in this analysis.

Table 2
Training and testing omission rates for minimum training presence (MTP), 10% training presence (10% TP), and sensitivity plus specificity threshold (SST) values for each time interval (0.5, 1, 2, 3, 4, 6, 8, and 12 h) evaluated in this study.

Interval (hour)	Type	Training omission rate	Test omission rate
	MTP	0.000	0.010
0.5	10% TP	0.071	0.097
	SST	0.175	0.198
	MTP	0.000	0.020
1	10% TP	0.057	0.055
	SST	0.159	0.137
	MTP	0.000	0.000
2	10% TP	0.089	0.038
	SST	0.125	0.057
	MTP	0.000	0.019
3	10% TP	0.077	0.019
	SST	0.308	0.250
	MTP	0.000	0.000
4	10% TP	0.100	0.156
	SST	0.283	0.222
	MTP	0.000	0.000
6	10% TP	0.098	0.222
	SST	0.223	0.296
	MTP	0.000	0.000
8	10% TP	0.077	0.000
	SST	0.192	0.080
	MTP	0.000	0.000
12	10% TP	0.100	0.117
	SST	0.101	0.117

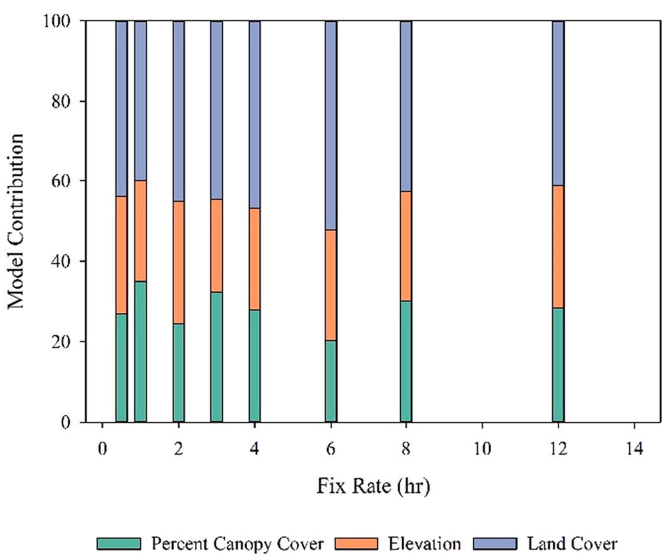

Fig. 4. Differences in covariate contributions for each time interval dataset model (0.5 to 12 h) were evaluated in the analysis.

in their data while retaining spatial independence between successive locations. This methodology is transferable across highly mobile terrestrial taxa and may allow researchers the ability to identify appropriate intervals to use when estimating ENMs at regional or continental spatial scales. Further, this approach can help inform species management or conservation strategies by strengthening the support for use of such data sources in these types of ecological modeling frameworks.

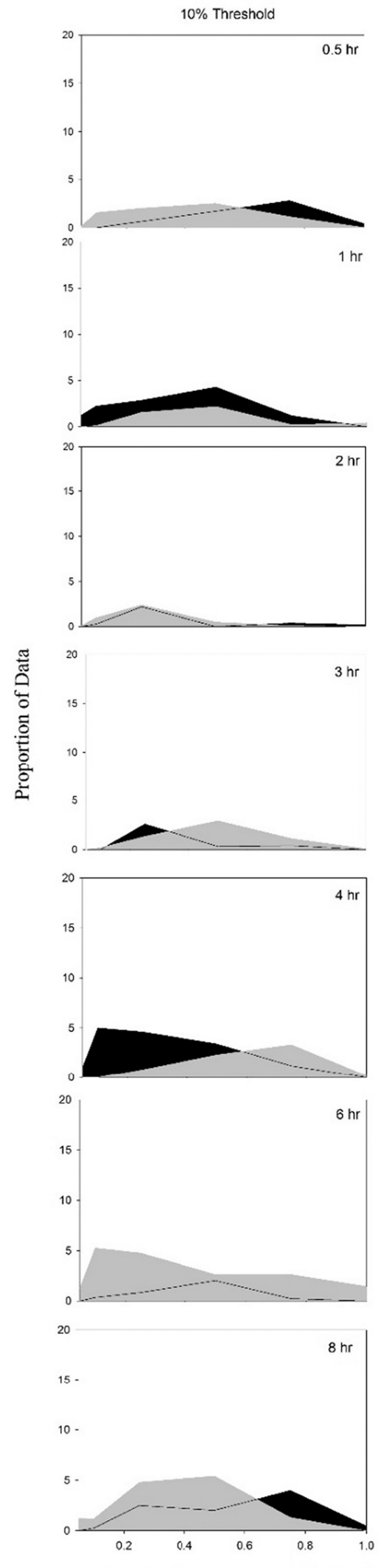

Fig. 5. The 10% threshold for under- and overestimation for GPS time interval (0.5, 1, 2, 3, 4, 6, and 8 h) compared to 12 h (baseline time interval).

Funding

The East Foundation provided financial support for the fieldwork aspect of this study. The Betty and George Coates Fellowship in Habitat Research, Phillip M. Plant, the South Texas Quail Coalition, Houston

Table 3
Estimated difference (%) in the spatial distribution of pixels of ocelot occurrence probabilities for each time interval (i.e., 0.5, 1, 2, 3, 4, 6, 8 h [hr]) compared to our baseline time interval (12h).

Difference	0.5 h	1 h	2 h	3 h	4 h	6 h	8 h
<−0.10	13.9	15.4	15.3	5.6	4.0	4.6	7.4
−0.1 - -0.5	7.6	19.3	9.9	10.9	16.7	10.4	28.1
0.5 - -0.05	55.0	55.8	60.0	76.8	73.8	53.0	53.2
0.05–0.10	14.2	6.2	8.3	3.5	2.4	20.2	5.8
>0.10	9.3	3.4	6.6	3.2	3.1	11.9	5.5

Safari Club, Ben F. Vaughn III, Tim and Karen Hixon Foundation, and Rene Barrientos provided financial support to JVL for this research.

Availability of data and material

Spatial data (Landsat 8) were obtained freely from the US Geological Survey. Raw GPS data contained possible identifying and sensitive location information and US-Endangered ocelot telemetry locations are to remain confidential as per the United States Fish and Wildlife Service federal regulations for ocelot research (permit number #PRT-67681, Federal Register). Parties with a legitimate interest in obtaining GPS data for replication purposes may contact David Hewitt, Director of the Caesar Kleberg Wildlife Research Institute, at David.Hewitt@tamuk.edu.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We thank the Caesar Kleberg Wildlife Research Institute, Texas A&M University-Kingsville, and the East Foundation for logistical support over the course of this project. We thank the East Foundation for providing financial support for the fieldwork aspect of this study.We are appreciative of the field assistance provided by J. M. Korn, J. P. Leonard, J. Tamez, S. B. Carter, M. O. Hewitt, D. R. Taylor, P. J. Wied, L. I. Grassman Jr., A. Ortega Jr., D. Kunz, L. D. Balderas, T. Shirley, G. W. Watts III, E. Rulison, A. Caso, and S. Carvajal. Special thank you to A. M. Foley and L. I. Grassman, Jr. for reviewing and improving previous versions of this manuscript. This manuscript is #20-104 of the Caesar Kleberg Wildlife Research Institute and #04 of the East Foundation.

References

Anderson, R.P., González Jr., I., 2011. Species-specific tuning increases robustness to sampling bias in models of species distributions: an implementation with MaxEnt. Ecol. Model. 222, 2796–2811.

Baasch, D.M., Tyre, A.J., Millspaugh, J.J., Hygnstrom, S.E., Vercauteren, K.C., 2010. An evaluation of three statistical methods used to model resource selection. Ecol. Model. 221, 565–574.

Benson, J.F., Abernathy, H.N., Sikich, J.A., Riley, S.P., 2021. Mountain lions reduce movement, increase efficiency during the Covid-19 shutdown. Ecol. Sol. Evid. 2, e12093.

Beumer, L.T., van Beest, F.M., Stelvig, M., Schmidt, N.M., 2019. Spatiotemporal dynamics in habitat suitability of a large Arctic herbivore: environmental heterogeneity is key to a sedentary lifestyle. Glob. Ecol. Conserv. 18, e00647.

Boyce, M.S., Pitt, J., Northrup, J.M., Morehouse, A.T., Knopff, K.H., Cristescu, B., Stenhouse, G.B., 2022. Temporal autocorrelation functions for movement rates from global positioning system radiotelemetry data. Philos. Trans. R. Soc. B 365, 2213–2219.

Cagnacci, F., Boitani, L., Powell, R.A., Boyce, M.S., 2010. Animal ecology meets GPS-based radiotelemetry: a perfect storm of opportunities and challenges. Philos. Trans. R. Soc. B 365, 2157–2167.

Caso, A., 2013. Spatial differences and local avoidance of ocelot (*Leopardus pardalis*) and jaguarundi (*Puma yagouaroundi*) in northeast Mexico. 2013. In: Dissertation. Texas A&M University-Kingsville.

Chibeya, D., Wood, H., Cousins, S., Carter, K., Nyirenda, M.A., Maseka, H., 2021. How do African elephants utilize the landscape during wet season? A habitat connectivity analysis for Sioma Ngwezi landscape in Zambia. Ecol. Evol. 11, 14916–14931.

Coxen, C.L., Frey, J.K., Carleton, S.A., Collins, D.P., 2017. Species distribution models for a migratory bird based on citizen science and satellite tracking data. Glob. Ecol. Conserv. 11, 298–311.

Crase, B., Liedloff, A.C., Wintle, B.A., 2012. A new method for dealing with residual spatial autocorrelation in species distribution models. Ecography 35, 879–888. https://doi.org/10.1111/j.1600- 0587.2011.07138.x.

Cruz, P., De Angelo, C., Martínez Pardo, J., Iezzi, M.E., Varela, D., Di Bitetti, M.S., Paviolo, A., 2019. Cats under cover: habitat models indicate high dependency on woodlands by Atlantic forest felids. Biotrop. https://doi.org/10.1111/btp.12635.

Cuyckens, G.A.E., Pereira, J.A., Trigo, T.C., Da Silva, M., Gonçalves, L., Huaranca, J.C., Bou Pérez, N., Cartes, J.L., Eizirik, E., 2015. Refined assessment of the geographic distribution of Geoffrey's cat (*Leopardus geoffroyi*) (Mammalia: Felidae) in the Neotropics. J. Zool. 298, 285–292.

De Solla, S.R., Bonduriansky, R., Brooks, R.J., 1999. Eliminating autocorrelation reduces biological relevance of home range estimates. J. Anim. Ecol. 68, 221–234.

Dempsey, S.J., Gese, E.M., Kluever, B.M., Lonsinger, R.C., Waits, L.P., 2015. Evaluation of scat deposition transects versus radio telemetry for developing a species distribution model for a rare desert carnivore, the kit fox. PLoS One 10, e0138995.

D'Eon, R.G., Delparte, D., 2005. Effects of radio-collar position and orientation on GPS radio-collar performance, and the implications of PDOP in data screening. J. Appl. Ecol. 42, 383–388.

Dormann, C.F., 2007. Effects of incorporating spatial autocorrelation into the analysis of species distribution data. Glob. Ecol. Biogeogr. 16, 129–138.

Dray, S., Royer-Carenzi, M., Calgene, C., 2010. The exploratory analysis of autocorrelation in animal- movement studies. Ecol. Res. 25, 673–681.

Duscher, T., Nopp-Mayr, U., 2017. Species distribution modeling for the invasive raccoon dog (*Nyctereutes procyonoides*) in Austria and first range predictions for alpine environments. Arch. Biol. Sci. 69, 637–647.

Elith, J., et al., 2011. A statistical explanation of MaxEnt for ecologists. Divers. Distrib. 17, 43–57.

Fourcade, Y., Engler, J.O., Rödder, D., Secondi, J., 2014. Mapping species distributions with MaxEnt using a geographically biased sample of presence data: a performance assessment of methods for correcting sampling bias. PLoS One 9, e97122.

Gómez-Ramírez, M.A., Gutiérrez-González, C.E., López-González, C.A., 2017. Ocelots thrive in a non-typical habitat of northwestern Mexico. Endanger. Species Res. 32, 471–478.

Harveson, P.M., Tewes, M.E., Anderson, G.L., Laack, L.L., 2004. Habitat use by ocelots in South Texas: implications for restoration. Wildl. Soc. B. 32, 948–954.

Heard, D.C., Ciarniello, L.M., Seip, D.R., 2008. Grizzly bear behavior and global positioning system collar fix rates. J. Wildl. Manag. 72, 596–602.

Hebblewhite, M., Haydon, D.T., 2010. Distinguishing technology from biology: a critical review of the GPS telemetry data in ecology. Phil. T. R. Soc. B. 365, 2303–2312.

Hijmans, R.J., Phillips, S., Leathwick, J., Elith, J., Hijmans, M.R.J., 2017. Package 'dismo'. Circles 9, 1–68.

Hofman, M.P., Hayward, M.W., Heim, M., Marchand, P., Rolandsen, C.M., Mattisson, J., Urbano, F., Heurich, M., Mysterud, A., Melzheimer, J., Morellet, N., et al., 2019. Right on track? Performance of satellite telemetry in terrestrial wildlife research. PLoS One 14, e0216223.

Joly, K., Craig, T., Sorum, M.S., McMillan, J.S., Spindler, M.A., 2015. Moose movement patterns in the upper Koyukuk River drainage, northcentral Alaska. Alces 51, 87–96.

Kays, R., Crofoot, M.C., Jetz, W., Wikelsk, M., 2015. Terrestrial animal tracking as an eye on life and planet. Science. 348 https://doi.org/10.1126/science.aaa2478.

Kramer-Schadt, S., Niedballa, J., Pilgrim, J.D., Schröder, B., Lindenborn, J., Reinfelder, V., Stillfried, M., Heckmann, I., Scharf, A.K., Augeri, D.M., Cheyne, S.M., 2013. The importance of correcting for sampling bias in MaxEnt species distribution models. Divers. Distrib. 19, 1366–1379.

Lehnen, S.E., Sternberg, M.A., Swarts, H.M., Sesnie, S.E., 2021. Evaluating population connectivity and targeting conservation action for an endangered cat. Ecosphere 12, e03367.

Leonard, J.P., Tewes, M.E., Lombardi, J.V., Wester, D.B., Campbell, T.A., 2020. Effects of sun angle, lunar illumination, and diurnal temperature on temporal movement rates of sympatric ocelots and bobcats in South Texas. PLoS One 15 (4), e0231732.

Lichstein, J.W., et al., 2002. Spatial autocorrelation and autoregressive models in ecology. Ecolog. Monograp. 72 (3), 445–463.

Limiñana, R., Arroyo, B., Terraube, J., McGrady, M., Mougeot, F., 2015. Using satellite telemetry and environmental niche modelling to inform conservation targets for a long-distance migratory raptor in its wintering grounds. Oryx. 49, 329–337.

Lombardi, J.V., Perotto-Baldivieso, H.L., Sergeyev, M., Veals, A.M., Schofield, L., Young, J.H., Tewes, M.E., 2021. Landscape structure of woody cover patches for endangered ocelots in southern Texas. Remote Sens. 13, 4001.

MacKenzie, D.I., Nichols, J.D., Royle, J.A., Pollock, K.H., Bailey, L., Hines, J.E., 2017. Occupancy Estimation and Modeling: Inferring Patterns and Dynamics of Species Occurrence. Elsevier.

Merow, C., Smith, M.J., Silander Jr., J.A., 2013. A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. Ecography 36, 1058–1069.

Milspaugh J, J, Kesler C, D, Kays W, R, Gitzen A, R, Schulz H, J, Rota T, C, Bodinof M, C, Belant H, J, Keller A, B, 2012. Wildlife radiotelemetry and remote monitoring. Wildlife Techniques Manual 1 258–283.

Norwine, J., Kuruvilla, J., 2007. The changing climate of South Texas, 1900-2100: problems and prospects, impacts and implications. In: Center for Research Excellence in Science and Technology- Research on Environmental Sustainability in Semi-Arid Coastal Areas. A&M University– Kingsville, Texas.

Perotto-Baldivieso, H.L., Cooper, S.M., Cibils, A.F., Figueroa-Pagán, M., Udaeta, K., Black-Rubio, C.M., 2012. Detecting autocorrelation problems from GPS collar data in livestock studies. Appl. Anim. Behav. Sci. 136, 117–125.
Phillips, S.J., Anderson, R.P., Schapire, R.E., 2006. Maximum entropy modeling of species geographic distributions. Ecol. Model. 190, 231–259.
Phillips, S.J., Dudík, M., Elith, J., Graham, C.H., Lehmann, A., Leathwick, J., Ferrier, S., 2009. Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data. Ecol. Appl. 19, 181–197.
Poor, E.E., Scheick, B.K., Mullinax, J.M., 2020. Multiscale consensus habitat modeling for landscape level conservation prioritization. Sci. Rep. 10, 1–13.
Radosavljevic, A., Anderson, R.P., 2014. Making better maxent models of species distributions: complexity, overfitting and evaluation. J. Biogeogr. 41, 629–643.
Reynolds, T.D., Laundre, J.W., 1990. Time intervals for estimating pronghorn and coyote home ranges and daily movements. J. Wildl. Manag. 54, 316–322.
Schwager, M., Anderson, D.M., Butler, Z., Rus, D., 2007. Robust classification of animal tracking data. Comput. Electron. Agric. 56, 46–59.
Shipley, B.R., Bach, R., Do, Y., Strathearn, H., McGuire, J.L., Dilkina, B., 2022. megaSDM: integrating dispersal and time-step analyses into species distribution models. Ecography. https://doi.org/10.1111/ecog.05450.
Swihart, R.K., Slade, N.A., 1985. Influence of sampling interval on estimates of home-range size. J. Wildl. Manag. 49, 1019–1025.
Thalmann, S., Peck, S., Wise, P., Potts, J.M., Clarke, J., Richley, J., 2016. Translocation of a top-order carnivore: tracking the initial survival, spatial movement, home-range establishment and habitat use of Tasmanian devils on Maria Island. Austral. Mamm. 38, 68–79.
Václavík, T., Kupfer, J.A., Meentemeyer, R.K., 2012. Accounting for multi-scale spatial autocorrelation improves performance of invasive species distribution modelling (iSDM). J. Biogeogr. 39, 42–55.
Veals, A.M., Holbrook, J.D., Blackburn, A., Anderson, C.J., DeYoung, R.W., Campbell, T. A., Young Jr., J.H., Tewes, M.E., 2022. Multiscale habitat relationships of a habitat specialist over time: the case of ocelots (*Leopardus pardalis*) in South Texas from 1982 to 2017. Ecosphere. In press.
Walton, Z., Samelius, G., Odden, M., Willebrand, T., 2018. Long-distance dispersal in red foxes *Vulpes vulpes* revealed by GPS tracking. Eur. J. Wildl. Res. 64, 1–6.
Ward, C.L., 2016. Evaluation of Survey Techniques and Sightability for Pronghorn antelope (*Antilocapra americana*) in Texas. Thesis. Texas A&M University-Kingsville.
Wikelski, M., Davidson, S.C., Kays, R., 2020. Movebank: archive, analysis and sharing of animal movement data. None. www.movebank.org. (Accessed 1 July 2020).
Yackulic, C.B., Chandler, R., Zipkin, E.F., Royle, J.A., Nichols, J.D., Campbell Grant, E.H., Veran, S., 2013. Presence-only modeling using MAXENT: when can I trust the inferences? Methods Ecol. Evol. 4, 236–243.
Young, J.K., Golla, J., Draper, J.P., Broman, D., Blankenship, T., Heilbrun, R., 2019. Space use and movement of urban bobcats. Anim. 9, 275.