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RESEARCH ARTICLE

Old tricks-new opportunities: combining telemetry ellipses and landscape metrics to assess habitat spatial structure

Alison R. Menefee · Humberto L. Perotto-Baldivieso · William P. Kuvlesky Jr. · Leonard A. Brennan · J. Alfonso Ortega-S. · Michael T. Page · Julia K. Burchsted

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Abstract

Context Confidence ellipses are areas derived from telemetry data that can be used to assess daily habitat use when integrated with land cover spatial structure. Our goal was to assess the feasibility of using confidence ellipses derived from telemetry data to assess landscape structure.

Objectives Our objectives were (1) to identify the geometry of confidence ellipses that can be used in landscape level studies; and (2) to quantify landscape structure within confidence ellipses derived from telemetry data. We used Rio Grande wild turkeys (*Meleagris gallopavo intermedia*) as our model species.

Methods We simulated landscapes and clipped them using known confidence ellipse shapes. We then compared the clipped areas with values measured for our simulated landscapes using landscape metrics that describe landscape structure. We used these results to select ellipse derived from telemetry data to evaluate landscape structure used by wild turkeys during the breeding and wintering seasons in South Texas.

Results Ellipses with a low x/y ratio (< 0.38) had significant differences from simulated landscape measurements. This information was used to remove wild turkey ellipses that did not meet the simulation criteria. Our results suggest that wild turkeys in South Texas used larger, more aggregated and interconnected patches of woody cover during the wintering season than during the breeding season.

Conclusions Landscape simulations facilitate the understanding of how landscape sampling strategies may be affected by sampling shape models. The integration of wildlife telemetry data with landscape ecology approaches and remote sensing were important in identifying spatial patterns used by wildlife.

Keywords Confidence ellipses · Landscape ecology · Landscape metrics · Radiotelemetry · Simulations

A. R. Menefee · H. L. Perotto-Baldivieso (✉) · W. P. Kuvlesky Jr. · L. A. Brennan · J. A. Ortega-S. · M. T. Page · J. K. Burchsted
Caesar Kleberg Wildlife Research Institute, 700 University Blvd, MSC 218, Kingsville, TX 78363, USA
e-mail: Humberto.perotto@tamuk.edu

Introduction

Radiotelemetry has been used in wildlife studies for over 60 years to assess animal locations and habitat resources utilization (Cochran and Lord 1963; Hebblewhite and Haydon 2010). There have been numerous worldwide studies documented using radiotelemetry approaches and it has proven to be an effective tool to assess landscape spatial structure use by wildlife (e.g. White and Garrott 1986; Russo et al.

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1997; Belcher and Darrant 2004; Seryodkin et al. 2013). Prior to the late 1960s, radiotelemetry triangulations were assumed to be error-free (Heezen and Tester 1967). However, errors occur as a result of location error, mapping error, signal bounce, proximity of surrounding vegetation, terrain features, electromagnetic effects, animal movements, distance effects, and observer error (Withey et al. 2001). These errors result in imprecisions in variance around bearings, distance from radio-collared animals, and intersection angle of the final triangulation (Saltz and Alkon 1985). Although error polygons have been used to address these issues by providing a polygon around the initial triangulation that assumes the animal is somewhere within that polygon, they have been found to be a poor measure of accuracy (Withey et al. 2001). Habitat use can easily be misclassified when there are errors in triangulations (Samuel and Kenow 1992). Confidence ellipses are an alternative to error polygons and are considered the best error measurement for triangulations because they are more likely to provide a precise location even if one of the bearings is an outlier (White and Garrott 1990). Confidence ellipses set a threshold (95%) for which data to retain and which to disregard due to poor triangulations (Saltz 1994). Though much of the literature on telemetry mentions that authors accounted for error in their data, few studies mention the effects that the error will have on the statistical analysis to assess accuracy (Murakami and Mano 1998). As a result, the impacts that these ellipses have on telemetry studies is unknown. Confidence ellipses provide an area that may be used to assess the land cover spatial structure within the ellipse for a specific point in time and space. Confidence ellipses combined with landscape metrics that describe land cover spatial structure could provide significant insight into how species use their habitat based on telemetry data. Though home range studies focus on a large area assumed to encompass all of the needed resources for an animal to survive (Powell and Mitchell 2012), daily movement studies examine habitat use on a smaller scale, and typically focus on individual selection patterns (Byrne et al. 2014). Confidence ellipses would be useful to reanalyze decades of individual telemetry data locations from previous wildlife studies to gain a historical perspective of landscape level habitat use by species. Combined with remote sensing approaches, the analysis of landscape structure within ellipses could make several analyses comparable through time and provide new insights on habitat use.

Environmental changes at the landscape level can be monitored by integrating remote sensing approaches and geographic information systems (GIS) (Mata et al. 2018; Miller et al. 2019; Lombardi et al. 2020). Additionally, landscape metrics derived from these approaches have been commonly used to assess changes in vegetation and measure landscape structure by providing a link between landscape pattern and function (Perotto-Baldivieso et al. 2011; Kupfer 2012). Consequently, changes in the spatial configuration of landscapes can have impacts on wildlife populations and their interactions with the landscape (Gustafson et al. 1994; Moilanen and Nieminen 2002; Miller et al. 2019). Moreover, combined use of landscape ecology and remote sensing approaches allows us to quantify landscape structure and how changes in landscape structure can affect species' distribution and habitat use (Kuvlesky et al. 2020). This information may then be used to manage wildlife populations and provide specific recommendations on harvest limits, species habitat, and monitor populations.

The goal of our research was to assess the feasibility of using confidence ellipses derived from telemetry data to assess the available landscape structure for wildlife. The approach we used analyzed how sampling shape affects landscape metric variables and has implications for multiple facets of wildlife research when concerning the effects landscape spatial pattern has on daily habitat use. We used an integration of remote sensing data, telemetry approaches, and landscape metrics to revisit data collected in 2004 and 2005 to achieve the following objectives: (1) identify the geometry of confidence ellipses that can be used in landscape level studies; and (2) to quantify landscape structure within confidence ellipses derived from telemetry data for our model species during the breeding and wintering seasons. We hypothesized that confidence ellipses provide an area that can be used to quantify landscape structure based on individual locations. We used Rio Grande wild turkeys (hereafter 'wild turkeys'; *Meleagris gallopavo intermedia*) in South Texas, USA as our model species. Wild turkeys utilize herbaceous areas during the breeding season for foraging, breeding, nesting, and brood-rearing (Alldredge et al. 2014). During the wintering season, wild turkeys use areas characterized by mature trees that are used for roosting and foraging directly below the canopy, when wild turkeys typically are not moving large distances (Holdstock et al. 2005), and roosting habitat that permits unobstructed views of the surrounding landscape and protection from predators is a critical part of wild turkey habitat (Litton and Harwell 1995). Wild turkeys in Texas typically nest and rear poults from April to August (Hall et al. 2006) and breeding seasons may be directly associated with weather changes as early rainfall results in earlier nesting due to early sprouting of green vegetation, which results in more cover and food resources (Beasom and Pattee 1980). Wild turkeys in Texas have been found to consume over 90 food items and insects are the most common food source during the breeding season, followed by grasses, brush, and forbs (Quinton et al. 1980; Cathey et al. 2007).

Materials and methods

Study area

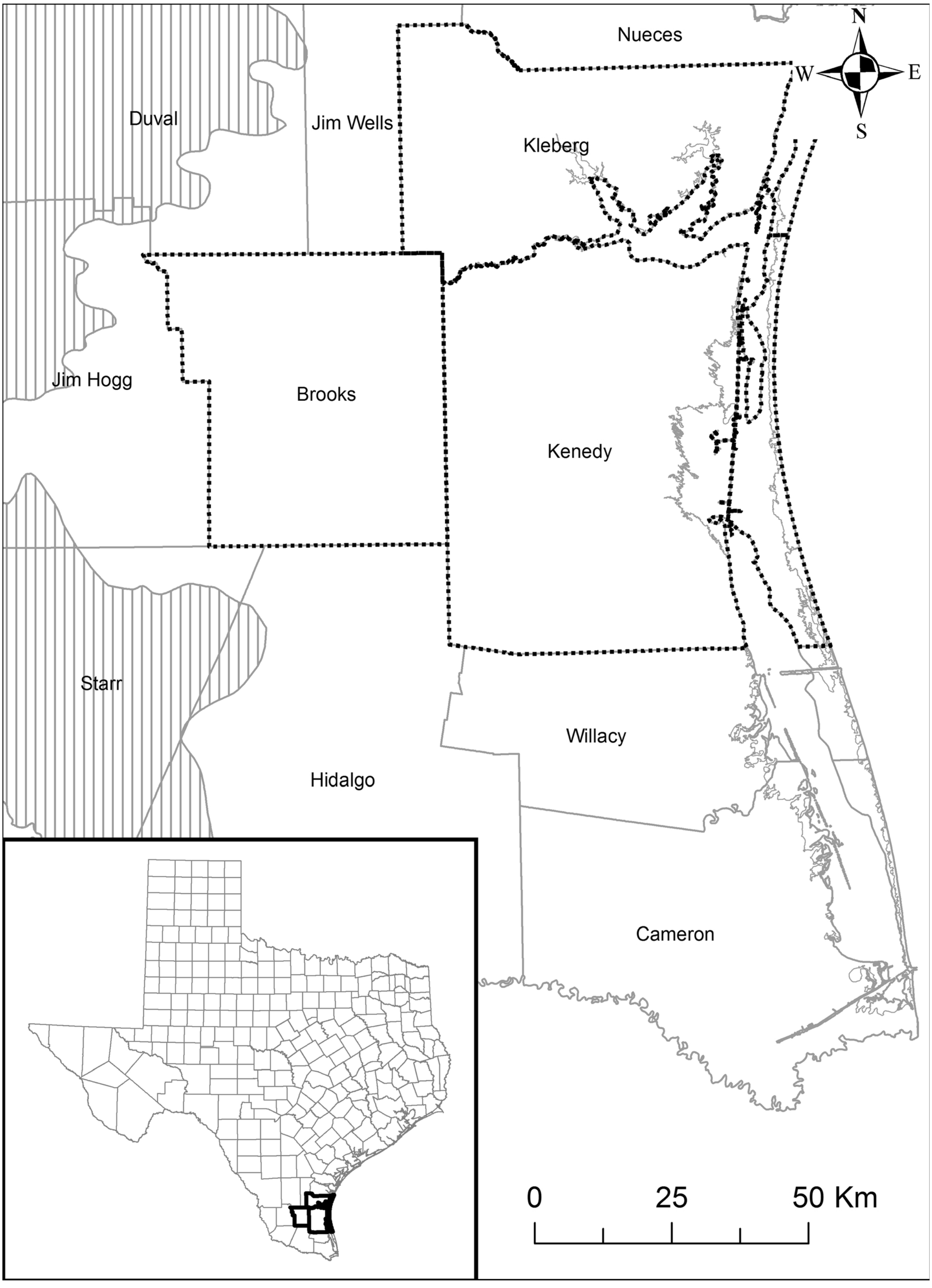
This study was conducted on the Encino, Laureles, and Norias divisions of the King Ranch in Brooks, Kenedy, and Kleberg counties (Fig. 1). These counties are located within the Western Gulf Coastal Plains ecoregion of Texas and encompasses portions of the three King Ranch divisions (Texas Parks and Wildlife Department 2018a). These areas are mixed-brush communities (Scifres 1980) comprised of dense vegetation dominated by seacoast bluestem (*Schizachyrium scoparium*), red lovegrass (*Eragrostis secundiflora*), yucca (*Yucca rupicola*), buffelgrass (*Cenchrus ciliaris*), indian blanket (*Gaillardia pulchella*), annual ragweed (*Ambrosia artemisifolia*), Texas croton (*Croton texensis*), granjeno (*Celtis pallida*), huisache (*Acacia farnesiana*), honey mesquite (*Prosopis glandulosa*) and Texas live oak (*Quercus fusiformis*) (Texas Parks and Wildlife Department 2018b; National Park Service 2019). Soils in the ecoregion are primarily sands, clay loams, and sandy loams (Fulbright et al. 1990). Rainfall in South Texas is sporadic and highly variable with peak rainfall occurring throughout May and June (Fulbright et al. 1990). Precipitation in the region annually averages 760 mm (National Oceanic and Atmospheric Administration 2018). Average temperatures throughout the year can range anywhere from 6 °C in the winter and frequently reach over 35 °C in the summer (US Climate Data 2020).

Data collection

We used telemetry data from a study conducted on female wild turkey during the wintering and breeding seasons in South Texas in 2004 and 2005 (Ramirez et al. 2012). Turkeys were fitted with backpack-style mortality-sensing transmitters (Advanced Telemetry Systems, Inc., Isanti, Minnesota), and locations were triangulated using hand-held Yagi antennas to locate 175 individuals 3–7 times/week throughout both years to collect diurnal and crepuscular movement data. We estimated telemetry locations and generated confidence ellipses areas drawn from triangulated coordinates using LOAS (Ecological Software Solutions, Sacramento, California). We generated a total of 946 ellipses, 180 during the winter season and 766 during the breeding season. We selected a confidence ellipse estimator with a small sample size correction at a 95% confidence level. Variables collected from LOAS were x-estimate, y-estimate, x-variance, y-variance, covariance, major axis, minor axis, and area. Major and minor axis variables were used to obtain aspect ratio values that directly correspond to the shape of each ellipse, while the area variable was used to filter the data based on daily movement values. These variables provided us with the needed information for data filtering.

Data simulation

To our knowledge, there is no study that has addressed how the shape of confidence ellipses may affect landscape sampling and the results derived from landscape metrics. While home range analyses are a common practice (Kie et al. 2010), not much has been done to quantify habitat use using confidence ellipses and landscape metrics based on individual locations gathered from telemetry locations. Our study used confidence ellipses to assess land cover patterns around an individual location instead of assessing the seasonal or annual patterns typical of home range studies. To date, aerial hexagon subsets have been found to be sufficient in estimating land cover types, though the small sample size of each block and sampling strategies may increase biases (Hunsaker et al. 1994; Hassett et al. 2012). To identify the



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◂**Fig. 1** Study area location. Counties in dashed outlines represent study area of the Norias, Laureles, and Encino divisions of the King Ranch in South Texas, USA. The study site was located in the Western Gulf coastal plains ecoregion. Vertical lines represent the Southern Texas Plains ecoregion

geometry of confidence ellipses that can be used in landscape level studies, we simulated 5 landscapes with different levels of spatial patterns using the modified random cluster method (Saura and Martínez-Millán 2000). This method simulates landscapes considered to be realistic and can be replicated with a wide range of spatial patterns. We generated our landscapes using a landscape categorical spatial pattern simulation software (Saura 2000; Saura and Martínez-Millán 2000) with a design consisting of landscapes with 5 levels of fragmentation (0.10, 0.25, 0.40, 0.55, 0.58; Fig. 2a) replicated 10 times. Fragmentation values corresponded to the degree of fragmentation and the number of patches in the simulated landscape. Level 0.10 demonstrates high levels of fragmentation, 0.40 medium levels, and 0.58 exhibits the lowest fragmentation levels (Saura 2000). We did not analyze levels of fragmentation above 0.593 as this is the percolation threshold value for 4-neighborhood analysis. Each landscape was simulated with a length of 1000 pixels, and 3 classes with equal proportion of class cover per landscape. Simulated landscapes were imported to GIS and pixel resolution was assigned to 1 m to emulate the spatial resolution of National Agriculture Imagery Program (NAIP) aerial photography. We created twelve ellipses (Fig. 2b) with an area of 30,000 m^2 each, which differed in shapes based on the ratio between the X-axis and the Y-axis (Table 1). A smaller aspect ratio results in a narrower ellipse (Fig. 3). This selected area value was sufficient to represent the area covered by the daily movement of female wild turkeys in South Texas (Byrne et al. 2014). We clipped the simulated landscapes to the shape of each ellipse (Fig. 2b) and calculated landscape metrics that describe wild turkey habitat landscape structure: percent woody cover (%), largest patch index (m^2), mean patch area (ha), aggregation index (%), edge density (m/ha), Euclidean nearest neighbor distance (m), and patch density (patches/100 ha) variables (Perotto-Baldivieso et al. 2011). Values of percent woody cover quantify abundance of patch types independent from each other; largest patch index reports the percentage of total area the largest patch encompasses; aggregation index calculates frequencies of different pairs of patch types; edge density calculates edge length per unit area; patch density refers to number of patches per unit area; and Euclidean nearest neighbor distance measures distance between patches of the same class (Gustafson and Parker 1992; Hargis et al. 1998; Hong et al. 2000). We used FRAGSTATS 4.2 (McGarigal et al. 2012) to quantify the simulated landscape structure and compared results from sampled areas to the values of the total area from the simulated landscapes using a linear mixed model using SAS 9.4. We tested the fixed effects of the ellipse clipped to the simulated landscapes, interaction of the entire simulated landscape and shape of the ellipse; random effects included replication within the simulated landscapes, an error term for the landscape effect, and a residual term. Normality of each error term was assessed using the Shapiro–Wilk (1965) test. Levene's (1960) test was used to test homogeneity of variances associated with the background effect. Mauchly's (1949) test was used to assess sphericity for the residual term. Normality assumptions were satisfied, but variances were heterogenous and sphericity was violated. Therefore, we used an unstructured variance–covariance matrix with replication of the background as the subject (Pinheiro and Bates 1996). When the simulated landscape and sampled shape interacted, simple main effects of shape within each level of the simulated landscape were tested, and each shape was compared to the simulated landscape with a t-test ($\alpha = 0.05$). We selected the ellipse shapes that were statistically similar to our simulated landscape results by selecting a threshold of the x/y ratio. Ellipses with ratios above 0.38 and below 1.00 were considered to have similar results to their respective landscapes.

Image classification

Forty National Agriculture Imagery Program (NAIP) digital ortho quad-quandrangles (DOQQ) were obtained through the Texas Natural Resources Information System (TNRIS) for 2004 to assess landscape structure. Images were classified using an unsupervised classification (ERDAS Imagine 2016) into three land cover classes: woody cover, herbaceous, and bare

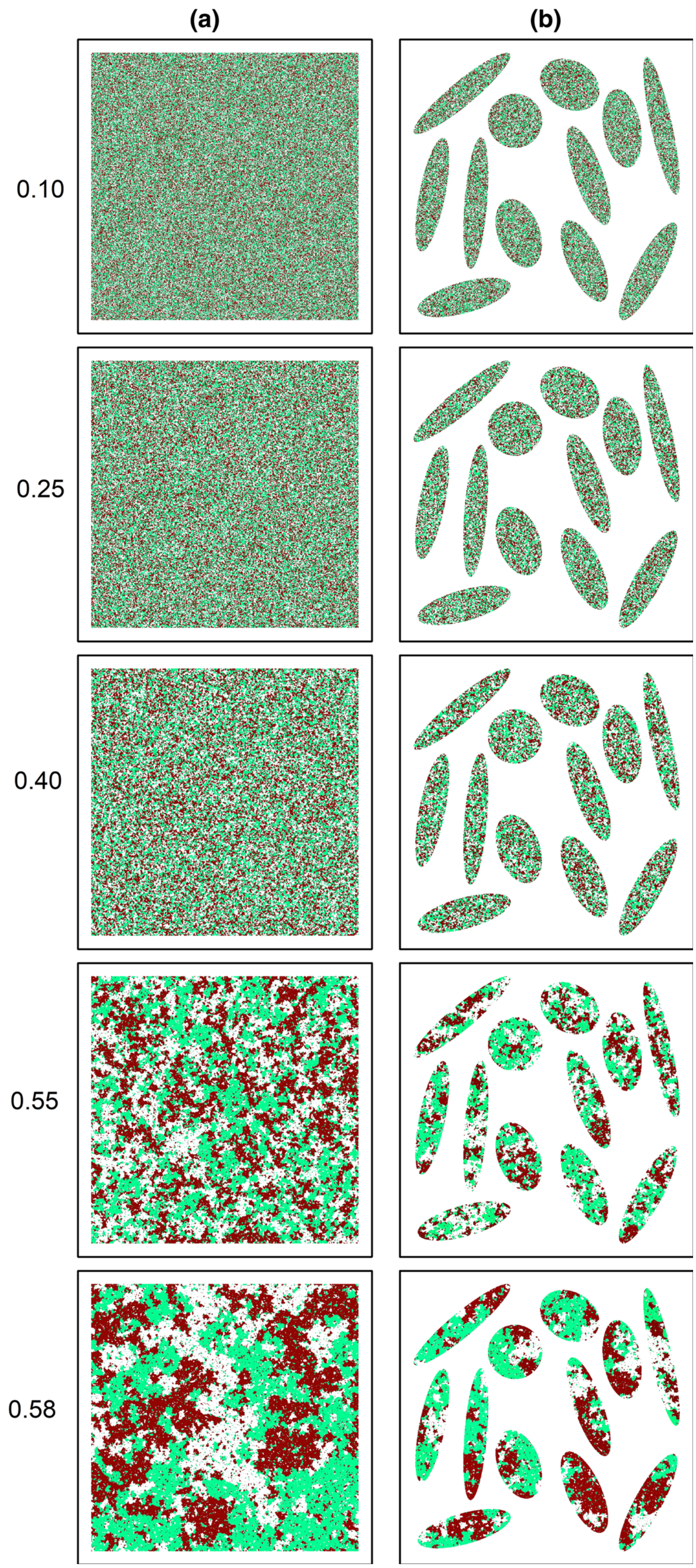


Fig. 2 Simulated landscapes for the five levels of fragmentation (0.10, 0.25, 0.40, 0.55, and 0.58) using three classes each distributed at 33% (**a**) and sampling ellipses with different aspect ratios derived from these simulated landscapes (**b**)

Table 1 Aspect ratios for twelve ellipses derived from the division of the major and minor axes when area is kept at 30,000 m^2

Aspect ratio	Major axis	Minor axis
0.15	37.89	252.00
0.17	40.29	237.00
0.19	43.01	222.00
0.22	46.13	207.00
0.24	48.47	197.00
0.27	51.07	187.00
0.32	55.52	172.00
0.38	60.82	157.00
0.47	67.25	142.00
0.59	75.19	127.00
0.76	85.26	112.00
1.00	97.00	97.00

ground following the methodologies described by Mata et al. (2018) for mapping land cover in the same region. Random points (200) were generated and used to conduct an accuracy assessment in each DOQQ (Foody 2009; Mata et al. 2018). Overall accuracy assessments were at least 85% for each classified DOQQ.

Landscape analysis

Using the telemetry data collected by Ramirez et al. (2012) we selected ellipses that had X/Y ratios equal or greater than 0.38 (Table 2), and areas that were < 30,000 m^2. We selected 106 ellipses out of 180 (70% total) during the winter season and 485 ellipses out of 766 (58% total) during the breeding season. We clipped the classified imagery using these ellipses and quantified woody cover spatial structure used by wild turkeys during the breeding and wintering seasons

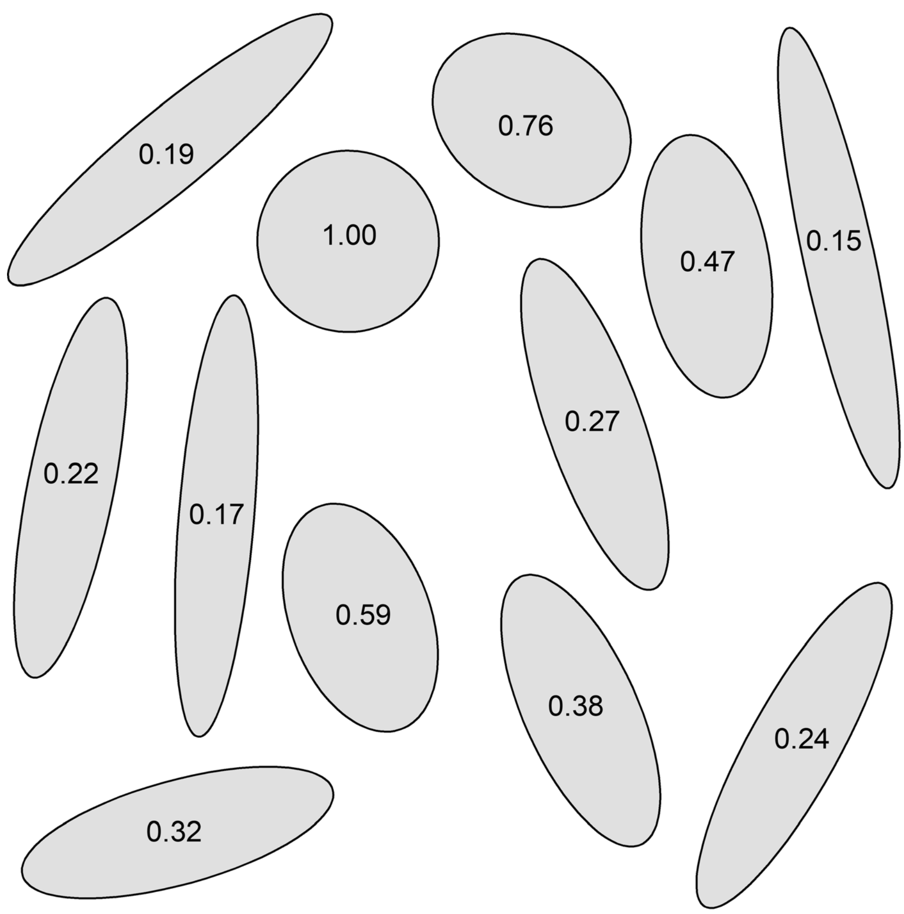


Fig. 3 Ellipse shapes used to sample simulated landscapes. The value inside each ellipse corresponds to the X/Y ration in Table 2

Table 2 The effect that low fragmentation pattern levels (0.55 and 0.58) have on landscape metric variables

Pattern level	Aspect ratio	Percent woody cover	Edge density	Largest patch index	Patch density	Mean patch area	Euclidean nearest neighbor distance	Aggregation index
0.10								
	0.15				x			
	0.17		x		x			
	0.19		x		x			
	0.22				x			
	0.24				x			
	0.27				x			
	0.32		x		x			
	0.38				x			
	0.47				x			
	0.59				x			
	0.76				x			
	1.00				x			
0.25								
	0.15		x		x			
	0.17				x			
	0.19				x			
	0.22				x			
	0.24				x			
	0.27				x			
	0.32				x			
	0.38				x			
	0.47				x			
	0.59							
	0.76							
	1.00							
0.40								
	0.15				x			
	0.17				x			
	0.19				x			
	0.22				x			
	0.24				x			
	0.27							
	0.32				x			
	0.38				x			
	0.47				x			
	0.59							
	0.76							
	1.00							
0.55								
	0.15			x	x			
	0.17			x				
	0.19			x			x	
	0.22			x				

Table 2 continued

Pattern level	Aspect ratio	Percent woody cover	Edge density	Largest patch index	Patch density	Mean patch area	Euclidean nearest neighbor distance	Aggregation index
	0.24			x				
	0.27			x				
	0.32	x	x	x	x	x		x
	0.38			x			x	
	0.47			x				
	0.59			x				
	0.76			x				
	1.00	x	x	x				
0.58								
	0.15	x	x	x		x		x
	0.17			x			x	x
	0.19	x		x	x			x
	0.22			x		x		
	0.24			x		x		x
	0.27			x			x	x
	0.32			x		x		
	0.38	x		x				x
	0.47			x		x		
	0.59			x				x
	0.76			x				x
	1.00		x	x			x	x

Pattern level of the simulated landscape and corresponding ellipse aspect ratios significant ($P < 0.05$) for each landscape metric

using the following metrics: percent woody cover, largest patch index, mean patch area, aggregation index, edge density, Euclidean nearest neighbor distance, and patch density for the following land cover types: woody, herbaceous, and bare ground (Perotto-Baldivieso et al. 2011). We compared the frequency distribution of woody cover spatial structure (i.e. landscape metrics) for wild turkeys in South Texas between breeding and wintering seasons using the Kolmogorov–Smirnov Z goodness of fit test with a significance level of 0.05 (Perotto-Baldivieso et al. 2011).

Results

Landscape metric variables were influenced ($P < 0.05$; DF = 540) most often at simulated pattern levels 0.55 and 0.58. However, all pattern levels had at least one difference between the metrics measured when comparing the simulated landscape to the corresponding ellipse (Table 1). Ellipses ratios of 0.22, 0.24, and 0.27 were also affected at pattern levels of 0.58. Of the seven-landscape metrics tested on the simulated ellipses, we found that largest patch index and patch density metrics corresponding to low fragmentation (pattern levels 0.55 and 0.58) were the most altered from the measured values of the landscape (Table 3). Shapes with aspect ratios of 0.15, 0.17, 0.19, and 0.32 had the most significant differences from the entire landscape measurements. We therefore selected ellipses that had aspect ratios between 0.38 and 1.00. While circular sampling methods are a common practice (Wheatley 2010; Schindler et al. 2013; Plexida et al. 2014), our simulation results show these had statistical differences ($P < 0.05$; DF = 540) from the landscape measurements.

Breeding season ellipses had lower mean values ($P < 0.05$; DF = 1) than wintering ellipses of percent woody cover (40.42% ± 2.22% and 53.51% ± 2.71%, respectively), largest patch index (29.27% ± 2.45% and 44.29% ± 3.13%, respectively), mean patch area (0.03 ha ± 0.0004 ha and 0.05 ha ± 0.007 ha, respectively), and aggregation index (76.85% ± 1.30% and 82.60% ± 1.26%, respectively) (Fig. 4). Values of patch density of breeding season ellipses exhibited higher values than wintering ellipses ($\bar{x}$=12,101 patches/ha ± 2427 patches/ha and 10,922 patches/ha ± 3226 patches/ha, respectively). These metrics suggest that wild turkeys in South Texas used larger, more aggregated and interconnected patches of woody cover during the wintering season than during the breeding season.

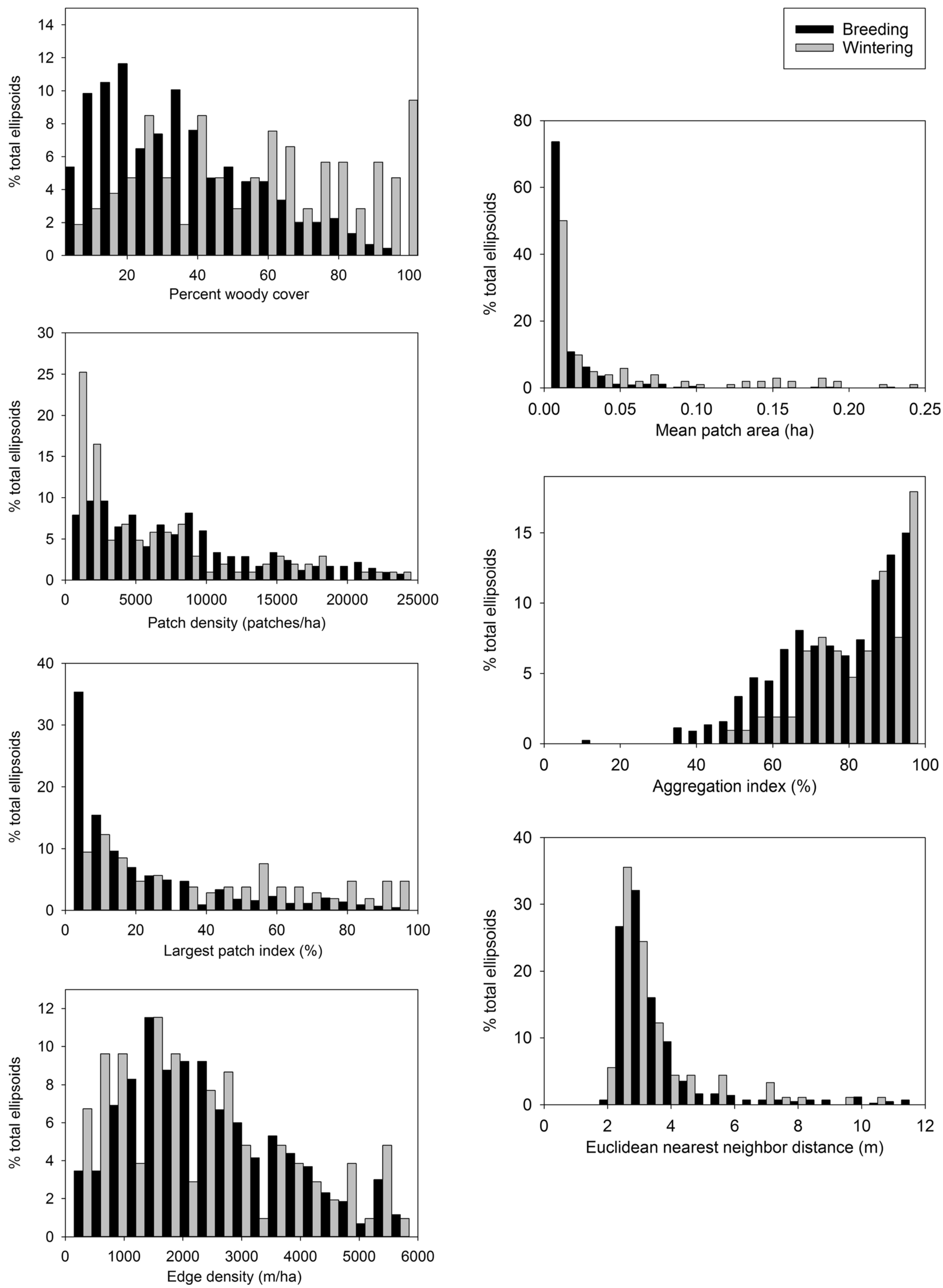
Discussion

Landscape simulations provided a robust approach to identify the shapes of ellipses that can be used to accurately represent landscape structure used by wildlife. We integrated telemetry data with landscape ecology and remote sensing principles in a new way to assess landscape structure with current remote sensing data and data gathered from telemetry locations in previous years. To achieve this, we simulated landscapes that allowed us to control single pieces of landscape characteristics (i.e. landscape size, fragmentation level, cover percentage). Simulations permit limitless replication, which may be useful in determining how different sampling strategies and variables influence metric outputs. Simulation analyses are not often done in reference to wildlife studies and instead often focus their ecological implications on climate change and natural catastrophes (Flato and Boer 2001; Uno and Kashiyama 2013; Wing et al. 2017). Moreover, simulated landscapes are useful to detect correlations between landscape patterns, spatial heterogeneity, and ecological processes (Gustafson and Parker 1992; With et al. 1997; Saura and Martínez-Millán 2000). Utilizing this simulation approach allowed us to identify sampling techniques that can be used to assess real data sets. While scale is known to influence the response of landscape metrics

Fig. 4 Frequency distributions of woody landscape metrics ▶ between breeding and wintering season ellipse created around female Rio Grande wild turkey telemetry locations in South Texas. Black bars represent breeding habitat and gray ones, wintering habitat

Table 3 Landscape metrics and aspect ratios affected (P < 0.05) for each significant index regardless of pattern level

Aspect ratio	Percent woody cover	Edge density	Largest patch index	Patch density	Mean patch area	Euclidean nearest neighbor distance	Aggregation index	Total ellipsoids affected
0.15	1	2	2	4	1		1	11
0.17		1	2	3		1	1	8
0.19	1	1	2	4		1	1	10
0.22			2	3	1			6
0.24			2	3	1		1	7
0.27			2	2		1	1	6
0.32	1	2	2	4	2		1	12
0.38	1		2	3		1	1	8
0.47			2	3	1			6
0.59			2	1			1	4
0.76			2	1			1	4
1.00	1	2	2	1		1	1	8
Total landscape metrics affected	5	8	24	32	6	5	10	


Breeding
Wintering
% total ellipsoids
Percent woody cover
Patch density (patches/ha)
Largest patch index (%)
Edge density (m/ha)
Mean patch area (ha)
Aggregation index (%)
Euclidean nearest neighbor distance (m)

(Moraga et al. 2019), landscape sampling shape and fragmentation levels also affect metric variables. Although circular sampling methods are the most commonly used sampling method (Wheatley 2010; Schindler et al. 2013; Plexida et al. 2014), it would instead be of benefit to use a slightly elliptical sampling strategy to accurately quantify landscape structure, as circular sampling strategies result in greater variances in the true landscape metric. Further research needs to address metrics behavior due to edge effects with different aspect ratio ellipses sampling strategies. Our results suggest that metrics for our gathered telemetry data would not be representative to capture overall landscape structure if we were to use ellipses that had aspect ratios below our identified threshold (X/Y ratio < 0.38).

The integration of landscape ecology approaches, wildlife techniques, and remote sensing were key to identifying the spatial patterns around species location data derived from telemetry data. This is supported by our results using wild turkeys to assess habitat use. There have been a long history of radiotelemetry studies dating back to the late 1950s to assess locations, movements, and home ranges of a variety of species across the world (LeMunyan et al. 1958; Loft and Kie 1988; Russo et al. 1997; Seryodkin et al. 2013). Though these studies, along with numerous others, have applied telemetry methods to various facets of wildlife research, telemetry specific errors have often been left out of the literature. Confidence ellipses combined with landscape metrics provided an approach to quantify the amount and spatial structure for how species use a landscape at a particular point in time. We have used this information to look at individual locations and analyze patterns of land cover data using wild turkeys as a model species. The approach we used was based on field data from 2004 and 2005 (Ramirez et al. 2012) to estimate home ranges, but that study did not include land cover information. Incorporating remote sensing data from 2004 allowed us to gain new insights on how land cover patterns influenced habitat use. Telemetry studies are often conducted with point data, which only captures the landscape characteristics in a single spot. Instead, by using confidence ellipses to look at landscapes around the location identified with telemetry, we are able to provide a proxy for how species use the landscape, which may be the first step in understanding historical datasets where field data and remote sensing information are available in order to quantify available areas of species-specific habitat for various wildlife species. The methods that we used are not only relevant to our studied species, but by understanding how landscape sampling shape will affect the inference of metric variables, we can re-analyze decades of wildlife data to understand how spatial patterns used by species have changed over time.

Conclusion

Landscape simulations facilitated our understanding of how landscape sampling strategies may be affected by sampling shape models. The integration of telemetry data from wildlife with landscape ecology approaches and remote sensing were important in identifying land cover spatial patterns around wild turkey locations in South Texas. The approaches used in this study can be applied to historical datasets where field data and remote sensing information are available in order to gain further insights into land cover patterns used by wildlife species.

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References

Alldredge BE, Hardin JB, Whiteside J, Isabelle JL, Parsons S, Conway WC, Cathey JC (2014) Eastern wild turkeys in Texas: biology and management. Texas AgriLife Extension publication WF-011. Texas A&M University, College Station, Texas, USA

Beasom SL, Pattee OH (1980) The effects of selected climatic variables on wild turkey productivity. Proc Natl Wild Turkey Symp 4:127–135

Belcher CA, Darrant JP (2004) Home range and spatial organization of the marsupial carnivore, *Dasyurus maculatus*

maculatus (Marsupialia: Dasyuridae) in south-eastern Australia. J Zool 262:271–280

Byrne ME, Guthrie JD, Hardin J, Collier BA, Chamberlain MJ (2014) Evaluating wild turkey movement ecology: an example using first-passage time analysis. Wildl Soc B 38:407–413

Cochran WW, Lord RD (1963) A radio-tracking system for wild animals. J Wildl Manag 27:9–23

Cathey JC, Melton K, Dreibelbis J, Cavney B, Locke SL, Demaso SJ, Collier B (2007) Rio Grande wild turkey in Texas: biology and management. Texas Cooperative Extension, Texas A&M University, College Station, Texas, USA

Flato GM, Boer GJ (2001) Warming asymmetry in climate change simulations. Geophys Res Lett 28:195–198

Foody GM (2009) Sample size determination for image classification accuracy assessment and comparison. Int J Remote Sens 30:5273–5291

Fulbright TE, Diamond DD, Rappole J, Norwine J (1990) The coastal sand plain of Southern Texas. Rangelands 12:337–340

Gustafson EJ, Parker GR (1992) Relationships between landcover proportion and indices of landscape spatial pattern. Landsc Ecol 7:101–110

Gustafson EJ, Parker GR, Backs SE (1994) Evaluating spatial pattern of wildlife habitat: a case study of the wild turkey (*Meleagris gallopavo*). Am Midl Nat 13:24–33

Hall GI, Butler MJ, Wallace MC, Ballard WB, Ruthven DC, Applegate HRL (2006) Rio Grande wild turkey home ranges in the southern Great Plains. Proc Southeastern Assoc Fish and Wildl Agencies 60:36–42

Hargis CD, Bissonette JA, David JL (1998) The behavior of landscape metrics commonly used in the study of habitat fragmentation. Landsc Ecol 13:167–186

Hassett EM, Stehman SV, Wickham JD (2012) Estimating landscape pattern metrics from a sample of land cover. Landsc Ecol 27:133–149

Hebblewhite M, Haydon DT (2010) Distinguishing technology from biology: a critical review of the use of GPS telemetry data in ecology. Philos Trans R Soc B 365(1550):2303–2312

Heezen KL, Tester JR (1967) Evaluation of radio-tracking by triangulation with special reference to deer movements. J Wildl Manag 31:124–141

Holdstock DP, Wallace MC, Ballard WB, Brunjes JH, Phillips RS, Spears BL, DeMasso SJ, Jernigan JD, Applegate RD, Gipson PS (2005) Male Rio Grande wild turkey habitat characteristics in the Texas panhandle and Southwestern Kansas. Proc Natl Wild Turkey Symp 9:217–229

Hong SH, DeZonia BE, Mladenoff DJ (2000) An aggregation index to quantify spatial patterns of landscapes. Landsc Ecol 15:591–601

Hunsaker CT, O'Neill RV, Jackson BL, Timmins SP, Levine DA, Norton DJ (1994) Sampling to characterize landscape pattern. Landsc Ecol 9:207–226

Kie JG, Matthiopoulos J, Fieberg J, Powell RA, Cagnacci F, Mitchell MS, Gaillard JM, Moorcroft PR (2010) The home range concept: are traditional estimators still relevant with modern telemetry technology. Philos Trans R Soc B 365:2221–2231

Kupfer JA (2012) Landscape ecology and biogeography: rethinking landscape metrics in a post FRAGSTATS landscape. Prog Phys Geogr 36:400–420

Kuvlesky WP, Brennan LA, Ortega-Santos JA et al (2020) Wild Turkeys in Texas: ecology and management. Texas A&M University Press, College Station

LeMunyan CD, White W, Nyberg E, Christian JJ (1958) Design of a miniature radio transmitter for use in animal studies. J Wildl Manag 23:107–110

Litton GW, Harwell F (1995) Rio Grande turkey habitat management. Texas Parks and Wildlife, Austin

Loft ER, Kie JG (1988) Comparison of pellet-group and radio triangulation methods for assessing deer habitat use. J Wildl Manag 52:524–527

Lombardi JV, Perotto-Baldivieso HL, Tewes ME (2020) Land cover trends in South Texas (1987–2050): potential implications for wild felids. Remote Sens 12:659

Mata JM, Perotto-Baldivieso HL, Hernández F, Grahmann ED, Rideout-Hanzak S, Edwards JT, Page MT, Shedd TM (2018) Quantifying the spatial and temporal distribution of tanglehead (*Heteropogon contortus*) on South Texas rangelands. Eco Process 7:2

McGarigal K, Cushman SA, Ene E (2012) FRAGSTATS V4: Spatial Pattern Analysis Program for Categorical and Continuous Maps. Computer software program produced by the authors at the University of Massachusetts, Amherst. http://www.umass.edu/landeco/research/fragstats/fragstats.html

Miller KS, Brennan LA, Perotto-Baldivieso HL, Hernández F, Grahmann ED, Okay AZ, Wu XB, Peterson MJ, Hannusch H, Mata J, Robles J, Shedd T (2019) Correlates of habitat fragmentation and northern bobwhite abundance in the Gulf Prairie landscape conservation cooperative. J Fish Wildl Manag 10:3–18

Moilanen A, Nieminen M (2002) Simple connectivity measures in spatial ecology. Ecology 83:1131–1145

Moraga AD, Martin AE, Fahrig L (2019) The *scale of effect* of landscape context varies with the species' response variable measured. Landsc Ecol 34:703–715

Murakami T, Mano T (1998) Improvement of errors in radiotelemetry locations of brown bears, *Ursus arctos*, in Hokkaido, Japan. Mamm Study 23:41–48

National Oceanic and Atmospheric Administration (2018) https://www.weather.gov/crp/localclimate#data. Accessed 12 April 2018

National Park Service (2019) Plants. https://www.nps.gov/pais/learn/nature/plants.htm. Accessed 18 July 2019

Perotto-Baldivieso HL, Wu XB, Peterson MJ, Smeins FE, Silvy NJ, Schwertner TW (2011) Flooding-induced landscape changes along dendritic stream networks and implications for wildlife habitat. Landsc Urban Plan 99:115–122

Pinheiro JC, Bates DM (1996) Unconstrained parametrizations for variance-covariance matrices. Stat Comput 6:289–296

Plexida SG, Sfougaris AI, Ispikoudis IP, Papanastasis VP (2014) Selecting landscape metrics as indicators of spatial heterogeneity—a comparison among Greek landscapes. Int J Appl Earth Obs 26:26–35

Powell RA, Mitchell MS (2012) What is a home range? J Mammal 93:948–958

Quinton DA, Montei AK, Flinders JT (1980) Brush control and Rio Grande turkeys in north-central Texas. J Range Manag 33:95–99

Ramirez ER, Clayton MC, Lawson CW, Burns SM, Guarneros-Altimirano R, DeMaso SJ, Kuvlesky WP, Hewitt DG, Ortega-Santos JA, Campbell TA (2012) Home ranges of female Rio Grande turkeys (*Meleagris Gallopavo Intermedia)* in Southern Texas. Southwest Nat 57:198–201

Russo L, Massei G, Genov PV (1997) Daily home range and activity of wild boar in a Mediterranean area free from hunting. Ethol Ecol Evol 9:287–294

Saltz D (1994) Reporting error measures in radio location by triangulation: a review. J Wildl Manag 58:181–184

Saltz D, Alkon PU (1985) A simple computer-aided method for estimating radio-location error. J Wildl Manag 49:664–668

Samuel MD, Kenow KP (1992) Evaluating habitat selection with radio-telemetry triangulation error. J Wildl Manag 56:725–734

Saura S (2000) SIMMAP 2.0 Landscape categorical spatial patterns simulation software. Page 20, Madrid

Saura S, Martínez-Millán J (2000) Landscape patterns simulation with a modified random clusters method. Landsc Ecol 15:661–678

Schindler S, Wehrden HV, Poirazidis K, Wrbka T, Kati V (2013) Multiscale performance of landscape metrics as indicators of species richness of plants, insects and vertebrates. Ecol Indic 31:41–48

Scifres CJ (1980) Brush management: principles and practices for Texas and the Southwest. Texas A&M University Press, College Station

Seryodkin IV, Kostyria AV, Goodrich JM, Miquelle DG (2013) Daily activity patterns of brown bear (*Ursus arctos*) of the Sikhote-Alin mountain range (Primorskiy Krai, Russia). Russ J Ecol 44:50–55

Texas Parks and Wildlife Department (2018a) Ecoregions of Texas. ftp://newftp.epa.gov/EPADataCommons/ORD/Ecoregions/tx/tx_eco_lg.pdf. Accessed 12 April 2018

Texas Parks and Wildlife Department (2018b) Plant guidance by ecoregions. https://tpwd.texas.gov/huntwild/wild/wildlife_diversity/wildscapes/ecoregions. Accessed 12 April 2018

Uno K, Kashiyama K (2013) Development of simulation system for the disaster evacuation based on multi-agent model using GIS. Tsinghua Sci Technol 13:348–353

U.S. Climate Data (2020) Weather averages. https://www.usclimatedata.com. Accessed 14 April 2020

Wheatley M (2010) Domains of scale in forest-landscape metrics: implications for species-habitat modeling. Acta Oceol 36:259–267

White GC, Garrott RA (1986) Effects of biotelemetry triangulation error on detecting habitat selection. J Wildl Manag 50:509–513

White GC, Garrott RA (1990) Analysis of wildlife radio-tracking data. Academic Press, San Diego

Wing AA, Emanuel K, Holloway CE, Muller C (2017) Convective self-aggregation in numerical simulations: a review. Surv Geophys 65:1–26

With KA, Gardner RH, Turner MG (1997) Landscape connectivity and population distributions in heterogeneous environments. Oikos 78:151–169

Withey JC, Bloxton TD, Marzluff JM (2001) Effects of tagging and location error in wildlife radiotelemetry studies. In: Radio tracking and animal populations, pp 43–70