RELATIONSHIP OF LESSER-PRAIRIE CHICKEN DENSITY TO LANDSCAPE CHARACTERISTICS IN TEXAS

by

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ABSTRACT

Ground-based lek surveys have traditionally been used to index trends in prairie grouse populations (*Centrocercus* and *Tympanuchus* spp.). However, indices of abundance or density can be fundamentally flawed and techniques that account for incomplete detection should be used. Distance sampling is a common technique used to estimate the density and abundance of animal populations and has been used with aerial surveys to monitor avian populations. With an increase in renewable energy development in native prairies and sagebrush steppe, there is a greater need to effectively monitor prairie grouse populations. One such species, the lesser prairie-chicken (LPC; *T. pallidicinctus*), has faced significant population declines and is thus, a species of conservation concern. In addition, much of the current and proposed wind energy development in the Great Plains overlaps some of the extant LPC distribution and few peer-reviewed studies have been conducted to investigate this potential disturbance to LPCs. Hierarchical distance sampling models can relate LPC lek density to landscape features and help predict the potential impact from wind and other energy development on lek density. Thus, the main objectives of our study were to estimate lek density in our sampling frame and to model anthropogenic and landscape features associated with lek density. We accomplished this by flying helicopter lek surveys for 2 field seasons and employing an aerial line-transect method developed at Texas Tech University.

We inventoried 208, 7.2 km × 7.2 km survey blocks and detected 71 new leks, 25 known leks, and observed 5 detections outside the current LPC range. We estimated 2.0 leks/100 km^2 (90% CI = 1.4–2.7 leks/100 km^2) and 12.3 LPCs/100 km^2 (90% CI = 8.5–

17.9 LPCs/100 km^2) for our sampling frame. Our state-wide abundance estimates were 293.6 leks (90% CI = 213.9–403.0 leks) and 1,822.4 LPCs (90% CI = 1,253.7–2,649.1 LPCs). Our best model indicated lek size and lek type (w_i = 0.235) influenced lek detectability. Lek detectability was greater for larger leks and natural leks rather than man-made leks. We used hierarchical distance sampling to build spatially-explicit models of lek density and landscape features. Our most competitive model included percent shrubland + paved road density + unpaved road density (AIC = 938.926, w_i = 0.826). Based on the spatially-explicit model, we estimated 248.5 leks (cv = 0.136) for our sampling frame. Lek density peaked when ≈50% of the landscape was composed of shrubland patches (i.e., shrubs <5 m tall comprising ≥20% of the total vegetation). This model also indicated an inverse relationship between lek density and paved and unpaved road densities. Our state-wide survey efforts provide wildlife managers and biologists with population estimates, new lek locations, and indicate landscape features that are related to lek density. Our spatially-explicit models predicted lek density based on percent shrubland and paved and unpaved road densities which can be used to predict how lek density may change in response to changes in habitat conditions and road densities.

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CHAPTER 1

INTRODUCTION

Ground-based lek surveys have traditionally been used to index trends in prairie grouse (*Centrocercus* and *Tympanuchus* spp.) populations (Cannon and Knopf 1981, Martin and Knopf 1981, Schroeder et al. 1992). However, indices of abundance or density can be fundamentally flawed because they often have poorly defined frames of inference, lack use of detection probabilities, or have poor sampling designs (Applegate 2000, Anderson 2001, Walsh et al. 2004, McRoberts et al. 2011*a*). Therefore, well-designed monitoring protocols that incorporate techniques which account for incomplete detection and have robust sampling designs should be used. Distance sampling is a common technique used to estimate the density and abundance of animal populations (Buckland et al. 2001) and has been used with aerial surveys to monitor avian populations (Butler et al. 2007, Rusk et al. 2007, Butler et al. 2008, McRoberts et al. 2011*a*). Recent advancements in analysis techniques for distance sampling surveys can provide managers with the ability to relate abundance with spatially-explicit covariates such as landscape or anthropogenic features (Hedley and Buckland 2004, Royle et al. 2004). These techniques allow for more hypothesis-driven monitoring that informs conservation decisions and actions (Nichols and Williams 2006).

With an increase in energy development in native prairies and sagebrush steppe (Hagen 2010, Naugle et al. 2011, Jarnevich and Laubhan 2011), there is a greater need to effectively monitor prairie grouse populations. One such species, the lesser prairie-chicken (LPC; *Tympanachus pallidicinctus*), has faced significant population declines and is currently a candidate species for Federal protection under the Endangered Species Act (ESA; Hagen et al. 2004). Much of the current and proposed wind energy development in the Great Plains overlaps some of the extant LPC distribution and few peer-reviewed studies have been conducted to investigate this potential disturbance (Kuvlesky et al. 2007, Hagen 2010). Spatially-explicit models can relate lek density to landscape features and help predict the potential impact from energy development on lek density (Hedley and Buckland 2004, Jarnevich and Laubhan 2011). Because wind energy development in the Texas Panhandle is imminent (Electric Reliability Council of Texas [ERCOT] 2006) and this development overlaps LPC occurrence in Texas (Brennan et al. 2009), the main objectives of our study were to estimate lek density and model anthropogenic disturbance and vegetative features associated with lek density. We accomplished this by flying helicopter-based surveys of leks for 2 field seasons in the Panhandle and employing a line-transect method (McRoberts et al. 2011*a*, *b*).

Lesser Prairie-Chickens

The occupied range of LPCs has been reduced by >90% and LPCs now inhabit fragments of native grassland in Colorado, Kansas, New Mexico, Oklahoma, and Texas (Fig. 1.1; Taylor and Guthery 1980). The reduced distribution of LPCs has been attributed to direct habitat loss from conversion of native grasslands for agriculture, livestock overgrazing, and encroachment of woody plants due to fire suppression, and indirect habitat loss from disturbance of oil and natural gas exploration and development

(Taylor and Guthery 1980, Braun et al. 1994, Applegate and Riley 1998, Hagen et al. 2004).

As a result, the LPC was petitioned for listing under the Endangered Species Act as threatened or endangered in 1995 and in 1998 the U.S. Fish and Wildlife Service (USFWS) determined that listing was "warranted, but precluded" (USFWS 1998). Recently, USFWS upgraded the listing priority for the LPC from a Priority 8 to a Priority 2 (USFWS 2008) suggesting that listing may be imminent (USFWS 1983). The listing priority was upgraded due to an "increased magnitude of threats" from oil and wind energy development, reversion of Conservation Reserve Program (CRP) to cropland, overgrazing, herbicide use in shinnery oak (*Quercus havardii*) habitat, mesquite (*Prosopis glandulosa*) and juniper (*Juniperus virginiana*) invasion, and habitat fragmentation (USFWS 2008). Given the LPC's conservation status, McRoberts et al. (2011*a*) identified a need for effective monitoring of LPC populations and the ability to find new leks, and they suggested the use of helicopter lek surveys to accomplish both needs.

Energy Development

An increase in renewable and non-renewable energy development could threaten the prairie grouse that inhabit native prairies and sagebrush steppe where there is high potential for wind and geothermal energy production and natural gas extraction (Hagen 2010, Jarnevich and Laubhan 2011, Naugle et al. 2011). For example, Texas currently produces the most wind power in the United States (e.g., 22.0% of the nation's total)

(American Wind Energy Association [AWEA] 2012) and 5 Competitive Renewable Energy Zones (CREZ) were designated in west Texas to encourage further wind energy development (ERCOT 2006). Transmission lines are already being constructed to deliver electricity from these zones to urban customers (ERCOT 2006) and the 2 CREZs in the Texas Panhandle overlap approximately 27% (3,288 km^2) of LPC occupied range (Fig. 1.2).

Several recent studies have examined the impacts of energy development on prairie grouse and many of these studies demonstrate avoidance of anthropogenic structures and human disturbance that leads to indirect habitat loss and fragmentation (Holloran 2005, Pitman et al. 2005, Walker et al. 2007, Doherty et al. 2008, Pruett et al. 2009*a*, *b*). For example, Holloran (2005) examined natural gas field development on greater sage-grouse (GSG; *C. urophasianus*) habitat selection, breeding behavior, and population dynamics in western Wyoming. He found that nesting hens avoided areas with a high density of active wells, the number of males displaying at leks decreased with increasing gas field-related disturbances around leks, and leks surrounded by gas field development had low juvenile male recruitment and high displacement of adult males. In a southwestern Kansas study, LPC nests were located further than expected from transmission lines or improved roads even though otherwise-suitable habitat surrounded these features (Pitman et al. 2005). Walker et al. (2007) examined GSG lek persistence in coal-bed natural gas (CBNG) fields and observed a greater decline in male attendance at leks and a decline in number of active leks compared to areas outside of CBNG fields. Doherty et al. (2008) also examined the impact of CBNG development on GSG and built a spatial model to identify suitable winter habitat. They found that GSG hens avoided CBNG development surrounded by suitable winter habitat.

Few peer-reviewed studies have investigated the potential impacts from constructing wind facilities and associated infrastructure on prairie grouse (Kuvlesky et al. 2007, Hagen 2010). After wind facility construction at 3 sites in Austria, local black grouse (*Lyrurus tetrix*) populations showed declining trends (Zeiler and Grünschachner-Berger 2009). Pruett et al. (2009*a*) examined the avoidance behavior of LPCs and greater prairie-chickens (GPC; *T. cupido*) to power lines and highways in northwestern and northeastern Oklahoma, respectively. Radio-marked LPCs avoided the power line in the study area by ≥100 m and few nests were found within 2 km of the power line. Greater prairie-chickens also appeared to avoid the power line in the study area and only 1 nest was found within 2 km. A large-scale study is currently being conducted in Wyoming to assess pre- and post-construction impacts of wind energy development on GSG habitat use at 3 wind facility sites (Johnson et al. 2011). A pre- and post-construction study was recently completed at 1 large wind facility in Kansas to examine impacts on GPCs, but results are not yet available (J. Pitman, personal communication, Kansas Department of Wildlife, Parks, and Tourism).

Population Monitoring

Ground-based lek surveys and lek counts have been used for many years to index population trends in prairie grouse populations (Cannon and Knopf 1981, Martin and Knopf 1981, Schroeder et al. 1992, Walsh et al. 2004, McRoberts et al. 2011*a*). Lek surveys are used to locate and count the number of active leks in a particular area, whereas lek counts measure the number of individuals at selected leks (McRoberts et al. 2011*b*). However, indices derived from lek surveys and counts can be fundamentally flawed due to incomplete detectability, changes in detection probability from year to year, and convenience-based sampling (e.g., road-based surveys; Applegate 2000, Anderson 2001, Walsh et al. 2004). Further, lek surveys conducted from the ground require many person-hours to cover large areas to search for leks (Grensten 1987, Martin and Knopf 1981, Schroeder et al. 1992) and road-based lek surveys may yield biased conclusions due to non-random sampling (Applegate 2000, McRoberts et al. 2011*a*). Other methods, such as mark-resight or aircraft-based surveys that deploy robust sampling designs and distance sampling to account for incomplete detection, may be used to obtain more accurate estimates of prairie grouse abundance or density (Walsh et al. 2004, McRoberts et al. 2011*a*).

Distance sampling is a common technique used to estimate the density and abundance of wildlife populations (Buckland et al. 2001). Density estimates for a study area are derived by estimating detection functions, which account for animals not detected in the survey area (Thompson 2002). Detection is modeled as a function of distance from detected objects to randomly-positioned transects or points and other covariates (Thompson et al. 1998, Buckland et al. 2001). Line transect surveys yield accurate density estimates when critical assumptions of distance sampling are met (e.g., objects are detected on the transect line with certainty, objects are detected at their initial location, detected objects are independent, and distance measurements are recorded without error; Buckland et al. 2001, Fewster et al. 2008). Studies should be designed to satisfy these assumptions by using random placement of transects throughout the study area, stratification of study area, obtaining adequate sample size, and providing a strict survey protocol for observers to follow (Buckland et al. 2001, Fewster et al. 2008).

If individuals are spatially clumped, the sampling frame may be stratified in which similar or adjacent sampling units are grouped together (e.g., similar habitat conditions, densities, or management objectives); random samples are then drawn from each stratum (Thompson et al. 1998). Stratification can also be a useful technique for targeting survey effort to areas important for management or conservation. Stratification usually results in higher precision, reduced bias in density estimates, and greater spatial coverage of the sampling frame (Thompson et al. 1998, Buckland et al. 2001). There are several ways to distribute sampling units among strata based on sampling costs, size of each stratum, and other sources of variation among strata. Strata-specific density estimates are often useful metrics, but density within the entire sampling frame (e.g., estimated as a weighted average) is important as well (Thompson et al. 1998, Buckland et al. 2001).

Aerial surveys have been widely used to monitor wildlife populations including avian species (Martin and Knopf 1981, Shupe et al. 1987, Pelletier and Krebs 1998, Butler et al. 2007, Pearse et al. 2008). As early as 1953, Eng (1955) flew aerial surveys for GSG leks from a fixed-wing aircraft. Compared to traditional ground-based surveys, aerial surveys allow a larger area to be sampled in less time (Grensten 1987) and access to remote or privately-owned land (Lehman and Mauermann 1963, Butler et al. 2007, McRoberts et al. 2011*a*). Helicopters have proven useful and reliable in aerial surveys for estimating Galliform bird densities (Shupe et al. 1987, Rusk et al. 2007, Butler et al. 2008) because they allow for reduced air speeds, sharper and safer turns between transects, and better vision directly below the aircraft as compared to fixed-wing aircraft (Grensten 1987, McRoberts et al. 2011*a*). Helicopters have been used to survey leks of GPCs (Schroeder et al. 1992), LPCs (McRoberts et al. 2011*a*), and Attwater's prairie chickens (*T. cupido attwateri*; Lehman and Mauermann 1963).

Recent studies have evaluated the use of aerial surveys and distance sampling to estimate avian density (Butler et al. 2007, Rusk et al. 2007, Butler et al. 2008). Rusk et al. (2007) compared density estimates of northern bobwhite (*Colinus virginianus*) in south Texas from morning covey-call surveys, walked transects, and helicopter transects. They found similar density estimates between the walked and helicopter transects. Butler et al. (2007) flew surveys from a fixed-wing aircraft for Rio Grande wild turkey (*Meleagris gallopavo intermedia*) to examine factors affecting flock detectability and test distance sampling assumptions. Their results indicated that flock size and vegetative cover had the greatest influence on detectability and fixed-wing aerial surveys may underestimate abundance. Butler et al. (2008) observed high wild turkey flock detectability from a helicopter and concluded that helicopter surveys were a practical tool for estimating wild turkey abundance.

During the spring of 2007 and 2008, a line-transect method was developed to measure LPC lek detectability and assess the disturbance response of lekking LPCs to 3 types of aircraft (McRoberts et al. 2011*a*, *b*). A Cessna 172 airplane, Robinson 22 helicopter, and Robinson 44 helicopter (hereafter, C172, R-22, and R-44, respectively) were used for the early-morning surveys. McRoberts et al. (2011*a*) found lek detectability was influenced by aircraft platform, distance, and lek type (e.g., man-made or natural). Specifically, leks attended by more males, man-made leks (e.g., abandoned oil and gas pads and bare ground surrounding stock tanks), and leks located closer to the transect were most visible from the R-44 (89.8%), followed by the R-22 (72.3%) and C172 (32.7%; McRoberts et al. 2011*a*). McRoberts et al. (2011*b*) also found no significant disturbance response from helicopter surveys on breeding LPCs and most LPCs that flushed in response to the helicopter resumed pre-disturbance activities within a 10-min period.

Spatial Modeling

Spatial models can relate landscape and anthropogenic features, such as percent grassland and road density, with animal abundance, density, or occurrence (Hedley and Buckland 2004, Jarnevich and Laubhan 2011). These models can identify suitable habitat and predict species occurrence or abundance, which is especially useful when balancing energy development and the needs of species of conservation concern, such as LPCs (Jarnevich and Laubhan 2011). Hamilton and Manzer (2011) developed resource selection function (RSF) models that accurately predicted sharp-tailed grouse (*T. phasianellus*) lek occurrence in east-central Alberta relative to broad landcover types. Jarnevich and Laubhan (2011) developed niche-based models (e.g., maximum entropy models; Elith et al. 2011) of habitat and anthropogenic features to predict the probability of LPC lek occurrence in Kansas to guide energy development.

Occupancy models (e.g., maximum entropy models) developed from convenience-based sampling without a formal survey design incorporate presence-only data; while these data may be all that are available to research ecologists, the spatial models they produce can be misleading due to sampling bias (Elith et al. 2011, Royle et al. 2012). Well-designed surveys can eliminate sampling bias, and incomplete detectability of individuals can be accounted for with hierarchical distance sampling (HDS) and spatial distance sampling (SDS) models (Hedley and Buckland 2004, Royal et al. 2004). These models can then relate spatial covariates to animal density or abundance through regression techniques. Further, because these methods model spatial variation associated with density or abundance, the resulting estimates are often more precise (Katsanevakis 2007).

Spatial distance sampling models use a Poisson point process and parameters are estimated based on the conditional likelihood of observed detections; this likelihood is not easy to control, especially with complex functions (Hedley and Buckland 2004, Royle et al. 2004). In contrast, HDS uses a more straight-forward approach in which estimated parameters are based on the unconditional likelihood of observed detections and competitive models can be objectively selected with Akaike's Information Criterion (Burnham and Anderson 2002); this likelihood appears to be better-behaved for complex functions (Royle et al. 2004).

Other than the presumed extent of the current range, little is known about the current spatial distribution of LPC leks in the Texas Panhandle relative to landscape features, such as roads, transmission lines, and oil and natural gas development. Because wind energy development in the Texas Panhandle is imminent (ERCOT 2006) and this development overlaps LPC occurrence in Texas (Pruett et al. 2009*b*), spatial models are an attractive technique for explaining lek density in the Texas Panhandle relative to current landscape features. Further, they can offer predictions of how lek density may change with alterations in vegetation or increased energy development. This information is needed because LPC populations in Texas have faced steady declines during the past 100 years (Jackson and DeArment 1963, Sullivan et al. 2000) and are currently a candidate species for ESA listing. Therefore, the ultimate goals of this project were to estimate lek density and abundance in the Texas occupied range and model anthropogenic and landscape features associated with lek density. We accomplished these goals by flying helicopter lek surveys for 2 field seasons and employing a line-transect method (McRoberts et al. 2011*a*, *b*).

Preface

This thesis represents my own critical thinking, data analysis, interpretation, and writing ability. The following chapters are co-authored by Jennifer M. Timmer, Matthew J. Butler, Warren B. Ballard, Clint W. Boal, and Heather A. Whitlaw. Co-authorship was determined based on the guidelines outlined by Dickson et al. (1978) and Ballard (2005). My chapters are written in a format intended for submission to the Journal of Wildlife

Management (Block et al. 2011). Chapter I highlights the need for more effective monitoring of prairie grouse and the potential impact of energy development, particularly on LPCs in west Texas. Chapter II provides lek and LPC density and abundance estimates for the Texas Panhandle and Chapter III provides spatially-explicit models relating lek density to landscape features, such as roads and transmission lines. The information presented in my thesis is intended to assist wildlife managers, biologists, and energy developers provide more effective management of LPCs in Texas and minimize potential impacts of energy development on this species of conservation concern.

Literature Cited

American Wind Energy Association. 2012. U.S. Wind Industry: fourth quarter 2011 market report. American Wind Energy Association, Washington, D.C., USA.

Anderson, D. R. 2001. The need to get the basics right in wildlife field studies. Wildlife Society Bulletin 29:1294−1297.

Applegate, R. D. 2000. Use and misuse of prairie chicken lek surveys. Wildlife Society Bulletin 28:457−458.

Applegate, R. D., and T. Z. Riley. 1998. Lesser prairie-chicken management. Rangelands 20:13−15.

Ballard, W. B. 2005. Determining authorship. Wildlife Society Bulletin 33:801.

Block, W. M., F. R. Thompson, D. Hanseder, A. Cox, and A. Knipps. 2011. Journal of Wildlife Management Guidelines. <http://joomla.wildlife.org/documents/JWMguidelines2011>. Accessed 27 Nov 2011.

Braun, C. E., K. Martin, T. E. Remington, and J. R. Young. 1994. North American grouse: issue and strategies for the 21st century. Transactions of the North American Wildlife and Natural Resources Conference 59:428–438.

Brennan, L. A., R. M. Perez, S. J. DeMaso, B. M. Ballard, and W. P. Kuvlesky, Jr. 2009. Potential impacts of wind farm energy on upland game birds: questions and concerns. Proceedings of the Fourth International Partners in Flight Conference: Tundra to Tropics 4:179–183.

Buckland, S. T., D. R. Anderson, K. P. Burnham, J. L. Laake, D. L. Borchers, and L. Thomas. 2001. Introduction to distance sampling: estimating abundance of biological populations. Oxford University Press, New York, New York, USA.

Burnham, K. P., and D. R. Anderson. 2002. Model selection and multimodel inference: a practical information-theoretic approach. Second edition. Springer, New York, New York, USA.

Butler, M. J., W. B. Ballard, M. C. Wallace, S. J. DeMaso, and B. K. McGee. 2007. Aerial surveys for estimating wild turkey abundance in the Texas Rolling Plains. Journal of Wildlife Management 71:1639–1645.

Butler, M. J., W. B. Ballard, M. C. Wallace, and S. J. DeMaso. 2008. Wild turkey (*Meleagris gallopavo*) detectability from helicopters and ramifications for estimating abundance. European Journal of Wildlife Research 54:148–152.

Cannon, R. W., and F. L. Knopf. 1981. Lek numbers as a trend to prairie grouse populations. Journal of Wildlife Management 45:776−778.

Davis, D. M., R. E. Horton, E. A. Odell, R. D. Rogers, and H. A. Whitlaw. 2008. Lesser prairie-chicken conservation initiative. Lesser Prairie-Chicken Interstate Working Group. Unpublished Report. Colorado Division of Wildlife, Fort Collins, USA.

Dickson, J. G., R. N. Connor, and K. T. Adair. 1978. Guidelines for authorship of scientific articles. Wildlife Society Bulletin 6:260–261.

Doherty, K. E., D. E. Naugle, B. L. Walker, and J. M. Graham. 2008. Greater sage-grouse winter habitat selection and energy development. Journal of Wildlife Management 72:187−195.

Electric Reliability Council of Texas. 2006. Analysis of transmission alternatives for Competitive Renewable Energy Zones in Texas. Electric Reliability Council of Texas, Austin, Texas, USA.

Elith, J., S. J. Phillips, T. Hastie, M. Dudik, Y. E. Chee, and C. J. Yates. 2011. A statistical explanation of MaxEnt for ecologists. Diversity and Distributions 17:43–57.

Eng, R. L. 1955. Use of aerial coverage in sage grouse strutting ground counts. Proceedings of the Annual Conference of Western Association of State Game and Fish Commissioners 34:231–233.

Fewster, R. M., C. Southwell, D. L. Borchers, S. T. Buckland, and A. R. Pople. 2008. The influence of animal mobility on the assumption of uniform distances in aerial line-transect surveys. Wildlife Research 35:275─288.

Grensten, J. J. 1987. Locating sharp-tailed grouse leks from color infrared aerial photography. Technical Note 377, Bureau of Land Management, Malta, Montana, USA.

Hagen, C. A., B. E. Jamison, K. M. Giesen, and T. Z. Riley. 2004. Guidelines for managing lesser prairie-chicken populations and their habitats. Wildlife Society Bulletin 32:69−82.

Hagen, C. A. 2010. Impacts of energy development on prairie grouse ecology: a research synthesis. Transactions of the 75th North American Wildlife and Natural Resources Conference 75:96−103.

Hamilton, S. and D. Manzer. 2011. Estimating lek occurrence and density for sharp-tailed grouse. Pages 31-49 *in* B. K. Sandercock, K. Martin, and G. Segelbacher, editors. Ecology, conservation, and management of grouse. Studies in Avian Biology, University of California Press, Berkeley, USA.

Hedley, S. L., and S. T. Buckland. 2004. Spatial models for line transect sampling. Journal of Agricultural, Biological, and Environmental Statistics 9:181−199.

Holloran, M. J. 2005. Greater sage-grouse (*Centrocercus urophasianus*) population response to natural gas field development in western Wyoming. Dissertation, The University of Wyoming, Laramie, USA.

Jackson, A.S., and R. DeArment. 1963. The lesser prairie chicken in the Texas Panhandle. Journal of Wildlife Management 27:733−737.

Jarnevich, C. S., and M. K. Laubhan. 2011. Balancing energy development and conservation: a method utilizing species distribution models. Environmental Management 47:926–936.

Johnson, G., C. LeBeau, and M. Halloran. 2011. Greater sage-grouse habitat use and population demographics at the Simpson Ridge Wind Resource Area, Carbon county, Wyoming. Pages 38-44 *in* S. S. Schwartz, editor. Proceedings of the Wind Wildlife Research Meeting VIII. RESOLVE, Inc. National Wind Coordinating Collaborative VIII, Washington, D.C., USA.

Katsanevakis, S. 2007. Density surface modeling with line transect sampling as a tool for abundance estimation of marine benthic species: the *Pinna nobilis* example in a marine lake. Marine Biology 152:77–85.

Kuvlesky, W. P., L. A. Brennan, M. L. Morrison, K. K. Boydston, B. M. Ballard, and F. C. Bryant. 2007. Wind energy development and conservation: challenges and opportunities. Journal of Wildlife Management 71:2487−2498.

Lehmann, V. W., and R. G. Mauermann. 1963. Status of Attwater's prairie chicken. Journal of Wildlife Management 27:713–725.

McRoberts, J. T., M. J. Butler, W. B. Ballard, H. A. Whitlaw, D. A. Haukos, and M. C. Wallace. 2011*a*. Detectability of lesser prairie-chicken leks: a comparison of surveys from aircraft. Journal of Wildlife Management 75:771−778.

McRoberts, J. T., M. J. Butler, W. B. Ballard, M. C. Wallace, H. A. Whitlaw, D. A. Haukos. 2011*b*. Response of lesser prairie-chickens on leks to aerial surveys. Wildlife Society Bulletin 35:27–31.

Martin, S. A., and F. L. Knopf. 1981. Aerial survey of greater prairie chicken leks. Wildlife Society Bulletin 9:219−221.

Naugle, D. E., K. E. Doherty, B. L. Walker, M. J. Holloran, and H. E. Copeland. 2011. Energy development and greater sage-grouse. Pages 489-503 *in* S. T. Knicks and J.W. Connelly, editors. Greater sage-grouse: ecology and conservation of a landscape species and its habitats. Studies in Avian Biology, University of California-Press, Berkeley, California, USA.

Nichols, J. D., and B. K. Williams. 2006. Monitoring for conservation. Trends in Ecology and Evolution 21:668–673.

Pearse, A. T., S. J. Dinsmore, R. M. Kaminski, and K. J. Reinecke. 2008. Evaluation of an aerial survey to estimate abundance of wintering ducks in Mississippi. Journal of Wildlife Management 72:1413−1419.

Pelletier, L., and C. J. Krebs. 1998. Evaluation of aerial surveys of ptarmigan *Lagopus* species. Journal of Applied Ecology 35:941−947.

Pitman, J. C., C. A. Hagen, R. J. Robel, T. M. Loughin, and R. D. Applegate. 2005. Location and success of lesser prairie-chicken nests in relation to vegetation and human disturbance. Journal of Wildlife Management 69:1259–1269.

Pruett, C. L., M. A. Patten, and D. H. Wolfe. 2009*a*. Avoidance behavior by prairie grouse: implications for development of wind energy. Conservation Biology 23:1253−1259.

Pruett, C. L., M. A. Patten, and D. H. Wolfe. 2009*b*. It's not easy being green: wind energy and a declining grassland bird. BioScience 59:257−262.

Royle, J. A., D. K. Dawson, and S. Bates. 2004. Modeling abundance effects in distance sampling. Ecology 85:1591–1597.

Royle, J. A., R. B. Chandler, C. Yackulic, and J. D. Nichols. 2012. Likelihood analysis of species occurrence probability from presence-only data for modelling species distributions. Methods in Ecology and Evolution. doi: 10.1111/j.2041-210X.2011.00182.x

Rusk, J. P., F. Hernandez, J. A. Arredondo, F. Hernandez, F. C. Bryant, D. G. Hewitt, E. J. Redeker, L. A. Brennan, and R. L. Bingham. 2007. An evaluation of survey methods for estimating Northern bobwhite abundance in Southern Texas. Journal of Wildlife Management 71:1336−1343.

Schroeder, M. A., K. M. Giesen, and C. E. Braun. 1992. Use of helicopters for estimating numbers of greater and lesser prairie-chicken leks in Eastern Colorado. Wildlife Society Bulletin 20:106−113.

Shupe T. E., F. S. Guthery, and S. L. Beasom. 1987. Use of helicopters to survey Northern bobwhite populations on rangeland. Wildlife Society Bulletin 15:458−462.

Sullivan, R. M., J. P. Hughes, and J. E. Lionberger. 2000. Review of the historical and present status of the lesser prairie-chicken (*Tympanuchus pallidicinctus*) in Texas. The Prairie Naturalist 32:177−188.

Taylor, M. A., and F. S. Guthery. 1980. Status, ecology, and management of the lesser prairie chicken. General Technical Report RM−77, U.S. Department of Agriculture, Forest Service, Rocky Mountain Forest and Range Experimental Station, Fort Collins, Colorado, USA.

Thompson, W. L., G. C. White, and C. Gowan. 1998. Monitoring vertebrate populations. Academic Press, San Diego, California, USA.

Thompson, W. L. 2002. Towards reliable bird surveys: accounting for individuals present but not detected. Auk 119:18–25.

U.S. Fish and Wildlife Service. 1983. Endangered and threatened species listing and recovery priority guidelines. Federal Register 48:48098–48105.

U.S. Fish and Wildlife Service. 2008. Candidate status review. Federal Register 73:75179−75180.

U.S. Fish and Wildlife Service. 1998. Endangered and threatened wildlife and plants; 12-month finding for a petition to list the lesser prairie-chicken as threatened and designate critical habitat. Federal Register 63:31400–31406.

Walker, B. L., D. E. Naugle, and K. E. Doherty. 2007. Greater sage-grouse population response to energy development and habitat loss. Journal of Wildlife Management 71:2644−2654.

Walsh, D. P., G. C. White, T. E. Remington, and D. C. Bowden. 2004. Evaluation of the lek-count index for greater sage-grouse. Wildlife Society Bulletin 32:56−68.

Zeiler, H. P., and V. Grünschachner-Berger. 2009. Impacts of wind power plants on black grouse, *Lyrurus tetrix*, in alpine regions. Folia Zoologica 58:173−182.

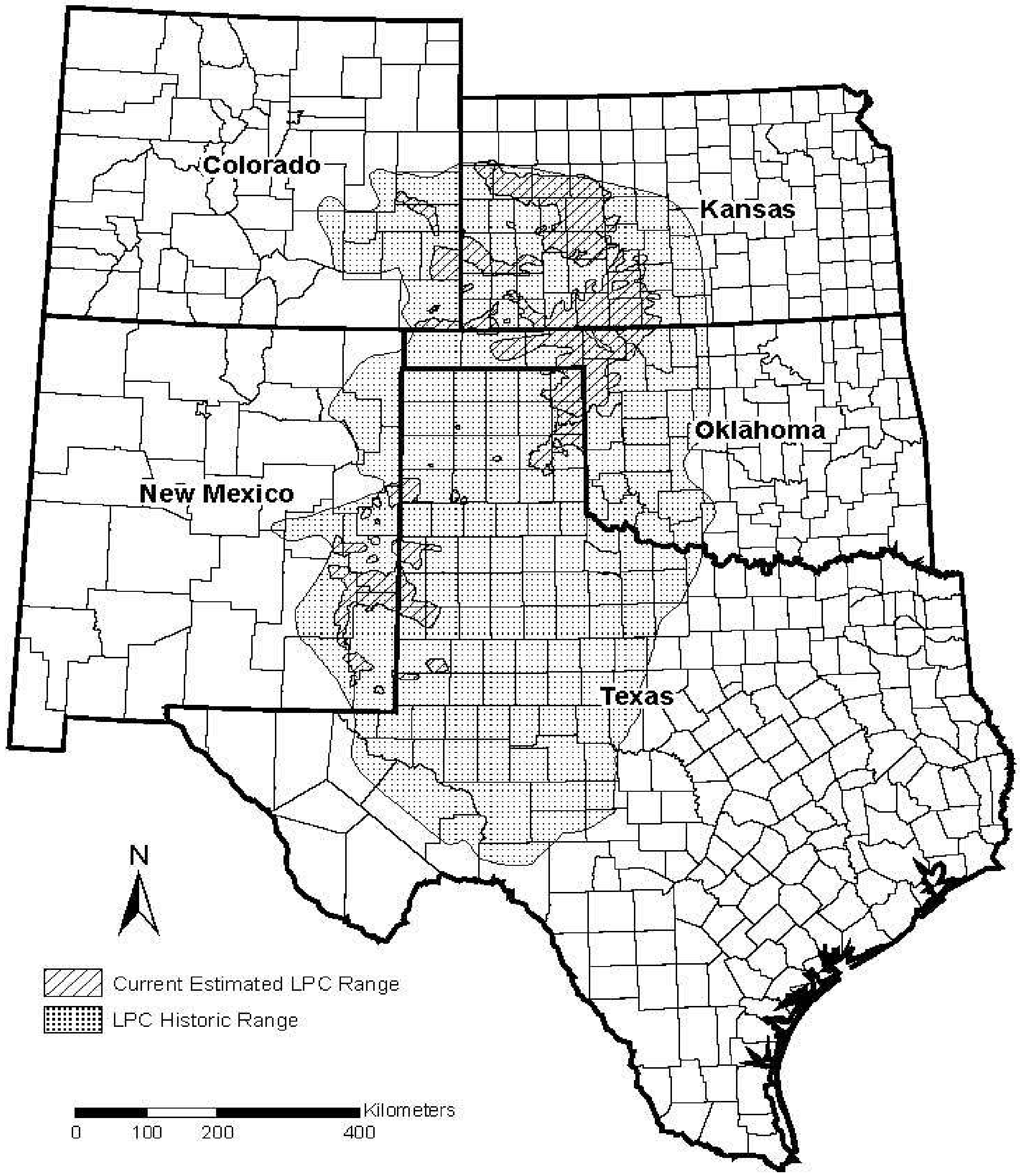

Figure 1.1. Map of the historic and the estimated 2007 occupied range for lesser prairie-chickens (based on Davis et al. 2008).

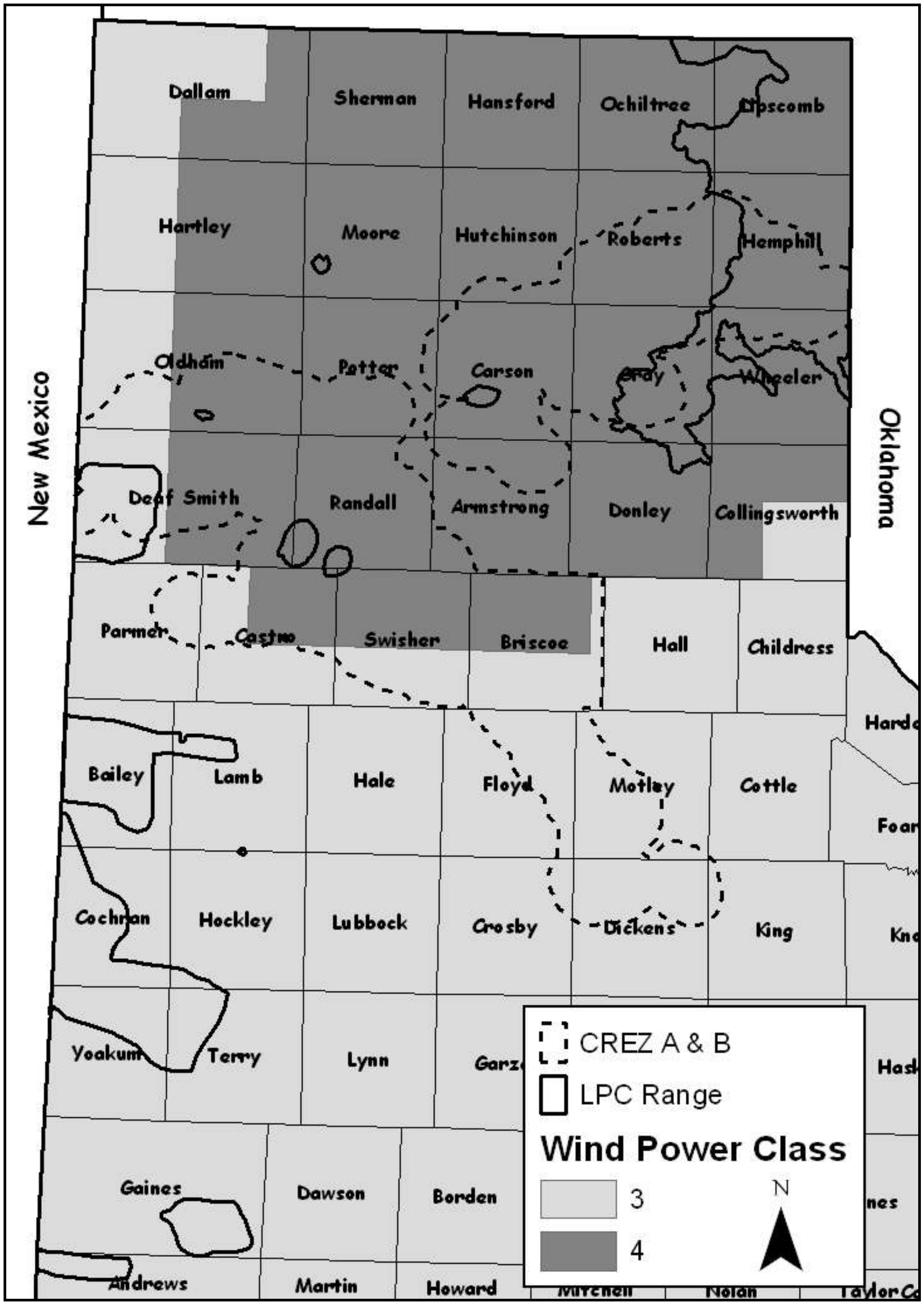

Figure 1.2. Current lesser prairie-chicken (LPC) range relative to wind power classes and Competitive Renewable Energy Zones (CREZ) in the Texas Panhandle.

CHAPTER II

ABUNDANCE AND DENSITY OF LESSER PRAIRIE-CHICKEN LEKS IN TEXAS

Abstract

As with many other grassland birds, lesser prairie-chickens (LPC; *Tympanuchus pallidicinctus*) have experienced population declines in the southern Great Plains. Their occupied range has been reduced by >90% due to direct habitat loss from conversion of native grassland to cropland, livestock overgrazing, and invasion of woody plants, and indirect habitat loss from disturbance by energy development. As a result, LPCs are a species of conservation concern. In Texas, LPCs have faced steady declines in the past 100 years and now face a new potential disturbance, wind energy development. Texas currently produces the most wind power in the United States and production is growing. In the Texas Panhandle, there are 2 declining LPC populations which may be negatively impacted by wind energy development. Thus, the main objective of this study was to determine the current density of LPC leks within the Texas occupied LPC range relative to potential wind energy development. Our sampling frame encompassed 86.9% of the Texas occupied LPC range (i.e., we excluded portions that were not LPC habitat such as riparian woodlands). To estimate lek density in our sampling frame, we employed a line-transect–based aerial survey method using a Robinson 22 helicopter to count leks. We surveyed a total of 26,810.9 km of aerial transects in the spring of 2010 and 2011 during which we detected 96 leks and observed 5 detections outside the currently delineated

LPC distribution. We estimated 2.0 leks/100 km^2 (90% CI = 1.4–2.7 leks/100 km^2) and 12.3 LPCs/100 km^2 (90% CI = 8.5–17.9 LPCs/100 km^2) for our sampling frame. Our state-wide abundance estimates were 293.6 leks (90% CI = 213.9–403.0 leks) and 1,822.4 LPCs (90% CI = 1,253.7–2,649.1 LPCs). Our best model indicated lek size and lek type (w_i = 0.235) influenced lek detectability. Lek detectability was greater for larger leks and natural leks versus man-made leks. Our state-wide survey efforts provided wildlife managers and biologists with population estimates, new lek locations, and areas to target for monitoring and conservation. This information is necessary for a species of concern, such as LPCs.

Introduction

The occupied range of lesser prairie-chickens (LPC; *Tympanuchus pallidicinctus*) has been reduced by >90% and LPCs now inhabit remnants of native grassland in Colorado, Kansas, New Mexico, Oklahoma, and Texas. This decline has been attributed to direct habitat loss from conversion of native grassland to cropland, livestock overgrazing, and invasion of woody plants, and indirect habitat loss from disturbance by energy development (Taylor and Guthery 1980, Applegate and Riley 1998, Hagen et al. 2004). As a result, the LPC was petitioned for listing under the Endangered Species Act (ESA) as threatened or endangered in 1995 (U.S. Fish and Wildlife Service [USFWS] 1998). Recently, USFWS upgraded listing priority from a Priority 8 to a Priority 2 (USFWS 2008) suggesting that listing may be imminent (USFWS 1983). The listing priority was upgraded to 2 because of an “increased magnitude of threats” from oil, natural gas, and wind energy development, reversion of Conservation Reserve Program (CRP) grassland to cropland, overgrazing, herbicide use in shinnery oak (*Quercus havardii*) habitat, mesquite (*Prosopis glandulosa*) and juniper (*Juniperus virginiana*) encroachment, and habitat fragmentation (USFWS 2008).

Due to the LPC's conservation status, McRoberts et al. (2011*a*) identified a need for effective monitoring and efficient techniques for finding new leks. Lek surveys and lek counts from the ground have traditionally been used to monitor population trends in prairie grouse (*Centrocercus* spp. and *Tympanachus* spp.) populations and have been incorrectly used to estimate population size (Applegate 2000, Walsh et al. 2004). In addition, lek surveys are often conducted from roads, a convenience-based sampling that can yield biased conclusions (Anderson 2001). Recent studies have evaluated the use of aerial surveys and distance sampling to estimate avian density (Butler et al. 2007, Rusk et al. 2007, Butler et al. 2008, McRoberts et al. 2011*a*). Aerial distance sampling provides a more accurate density estimate than the traditional ground-based techniques by allowing for probabilistic sampling of potential habitat and adjusting for incomplete detectability (Buckland et al. 2001). Compared to traditional ground surveys, aerial surveys allow a larger area to be sampled in less time and access to remote or privately-owned land (Butler et al. 2007, McRoberts et al. 2011*a*).

Texas currently produces the most wind power in the United States (American Wind Energy Association 2012) and 5 Competitive Renewable Energy Zones (CREZ) were designated in west Texas to encourage further wind energy development (Electric Reliability Council of Texas [ERCOT] 2006). Transmission lines are already being constructed to deliver electricity generated in these zones to customers in large Texas cities to the east (ERCOT 2006). Two of the CREZs overlap approximately 27% of the occupied LPC range in Texas. However, little is known about how this anthropogenic disturbance could impact LPC density which has faced steady declines during the past 100 years (Sullivan et al. 2000, Kuvlesky et al. 2007). To better inform conservation and management decisions, we conducted the first randomized line-transect–based distance sampling aerial survey of the Texas occupied LPC range. Our objective was to estimate lek density and abundance in Texas relative to potential wind energy development.

Study Area

The current estimated range of LPCs in Texas lies mostly in the northeast and southwest portions of the Texas Panhandle, with a few birds thought to be scattered throughout the central portion (Davis et al. 2008). Our sampling frame encompassed 86.9% of the Texas occupied LPC range (e.g., we excluded portions that were not LPC habitat such as riparian woodlands and cotton fields), while focusing on the intersection of current LPC range and the 2 CREZs. The northeast region of the study area was a mixed-grass prairie dominated by sand sagebrush (*Artemisia filifolia*) and little bluestem (*Schizachyrium scoparium*). The southwest region of the study area was a short-grass prairie dominated by shinnery oak (*Quercus havardii*) and little bluestem with some mesquite (*Prosopis glandulosa*). Cotton, winter wheat, and grain sorghum were the main crops grown in the region (United States Department of Agriculture [USDA] 2008). The climate of the Panhandle was mostly dry and the majority of the precipitation occurred during the fall and spring (PRISM Climate Group 2011). The southwest region of the Panhandle received an average of 40−51 cm of precipitation yearly and the northeast region received an average of 50−61 cm of precipitation yearly (PRISM Climate Group 2011).

Methods

We used a stratified random sampling design with 4 strata (Thompson et al. 1998). The 4 strata were based on vegetative characteristics thought to influence LPC density (e.g., grassland, shrubland, agriculture, and a mosaic) and potential for wind energy development impacts on LPCs. For example, areas composed mostly of native and CRP grasslands were grouped together into one stratum because LPCs use this habitat for breeding, nesting, and brood-rearing (Taylor and Guthery 1980, Applegate and Riley 1998). We delineated vegetation types based on the U.S. Department of Agriculture (USDA) Texas cropland data layer (USDA 2008). The sampling frame was divided into 329, 7.2 km × 7.2 km survey blocks. At this size, we could complete 1 survey block per flight.

The first stratum was composed of survey blocks that were within a CREZ and ≥50% grassland (patches were native grassland, CRP, or idle cropland comprising >80% of the total vegetation; Table 2.1). The second stratum was composed of survey blocks that were also ≥50% grassland, but not within a CREZ. The third stratum was composed of survey blocks with >50% shrubland (i.e., patches were composed of shrubs <5 m tall comprising ≥20% of the total vegetation) and this particular composition did not occur within a CREZ. The fourth stratum was composed of survey blocks with a ≥75%

combination of grassland/shrubland/grain field (this mosaic was comprised of 30–50% grassland, ≤50% shrubland, and >0% grain field) and 1 of these blocks was located within a CREZ. The specifications for this stratum were meant to include potential LPC habitat while excluding non-habitat, such as urban areas, water bodies, cotton fields, and woodland regions (e.g., riparian cottonwood [*Populus deltoides*] galleries).

We allocated sample size to each stratum using the following formula

$$u_i = U \times g_i$$

where u_i is the number of survey blocks allocated to each stratum i, U is the total number of survey blocks allocated for the 2-year study (initially 180 blocks) and g_i is the weighting factor for each stratum i. The weighting factor was calculated as

$$g_i = \frac{r_i}{\sum r_i}$$

where r_i was the rank for each stratum i. The strata were ranked from 1 to 4 with 4 representing the highest priority stratum. Because we were most interested in examining LPC density in areas subject to wind energy development, we prioritized the strata based on the greatest potential for wind energy development to impact lek distribution. We planned to survey 180 blocks over 2 survey years. Based on the weighting factors, we randomly-selected 72 survey blocks in the first stratum, 54 in the second stratum, 36 in the third stratum, and 18 in the fourth stratum (Table 2.1). We also selected some additional blocks from each stratum in case we were able to survey more blocks than planned.

We used ArcGIS 9.3 (Environmental Systems Research Institute, Inc., Redlands, CA) to create a set of grid cells (7.2 km × 7.2 km) over the extent of the occupied LPC range in Texas. We re-classified and grouped the landcover layer based on the Texas cropland data layer (USDA 2008) into 8 categories (e.g., cotton, grains, other crops, grassland or idle pasture, shrubland, woodland, open water, and barren or developed areas) and calculated the area of grassland, shrubland, and grain field in each survey block. We combined this information with the 2 CREZs in the Panhandle and assigned survey blocks to 1 of the 4 strata and then randomly-selected blocks from each stratum. Of the 329 survey blocks covering the sampling frame, we did not consider 44 blocks as potential LPC habitat because they were mostly urban, open water, or woodland), and so were not included in any strata.

We used ArcGIS 9.3 to generate a flight path for each survey block and measure the nearest distance from each detection to a transect (Hiby and Krishna 2001). Transects were oriented north-south with 400-m spacing between them. The observer's global positioning system (GPS) unit recorded a track log of each flight path to provide the actual transect lengths that were surveyed. We set the track logs to record points at least every 2 seconds.

We divided our sampling frame into 2 regions for the 2 field seasons. During spring 2010, we surveyed blocks in the northeast and central regions of the Panhandle (hereafter, northeast region) and during spring 2011, we surveyed blocks in the southwest and west-central regions (hereafter, southwest region; Fig. 2.1). We conducted our surveys from an R-22 helicopter (Robinson Helicopter Co., Torrance, CA), which seated the pilot and 1 observer. To train technicians, we also conducted flights early in each field season from an R-44 helicopter (Robinson Helicopter Co., Torrance, CA). We conducted flights between early-March and late-May 2010–2011. We followed the survey protocol developed by McRoberts et al. (2011*a*) (i.e., target altitude of 15 m above ground-level, target speed of 60 km/hr, survey between sunrise until ≈2.5 hr post-sunrise). We did not include portions of transects that were surveyed outside the set survey protocol (e.g., when the pilot increased the helicopter's altitude to avoid towns or feedlots) in the final analyses. When LPCs were detected, the pilot deviated from transect and flew over the center of the group of birds or the center of the location from where birds flushed. We used a GPS unit to record the exact location of detected LPCs.

After aerial surveys, we examined ≥50% of the aerial detections from the ground to verify lek activity and location. We arrived at detected leks ≥60 min before sunrise to listen for male vocalizations and watch for male displays. If LPCs were not seen or heard at or near the detection waypoints, we looked around the point within a ≈100–m radius for evidence of lek activity (e.g., feathers, scat, flattened grass, etc.). We conducted ground counts with binoculars from a parked vehicle or blind approximately 75–200 m from each lek (McRoberts et al. 2011*b*).

<u>Data Analysis</u>

We separated our data into 2 groups for analysis for each region: detections that were confirmed leks and all detections (i.e., lek and non-lek detections). To analyze the leks-only dataset, the individual lek was our sampling unit. For the all-detections dataset, each detection was a sampling unit and we analyzed our observations as groups of LPCs.

We used program R 2.13.0 (R Development Core Team 2011) to perform 2-way ANOVA tests with the strata and region as explanatory covariates and either average cluster size or average encounter rate as the response variable to determine if the data should be further stratified by region ($\alpha = 0.10$).

We grouped our distance data into 7 distance intervals, 0–35 m, 35–50 m, 50–70 m, 70–90 m, 90–120 m, 120–150 m, and 150–179 m, for both datasets (Fig. 2.2). We determined our grouping based on recommendations by Buckland et al. (2001) to reduce spiking around the centerline, produce a shoulder on the detection function, and provide better model fit.

We used the multiple-covariate and conventional distance sampling engines in program DISTANCE 6.0 (Thomas et al. 2010) to analyze our data and Akaike's Information Criterion corrected for small sample size (AIC_c) to select competitive models (Burnham and Anderson 2002). We considered models competitive if $\Delta AIC_c \leq 2$ and excluded models with uninformative parameters (Arnold 2010). For the leks-only dataset, our covariates included lek size, lek type, and survey date. We included lek size and lek type (i.e., man-made or natural) in our models because McRoberts et al. (2011*a*) determined that lek detectability was greater for man-made leks and larger leks. For our analysis, man-made leks included leks located in grain or plowed fields because the vegetation was shorter in these manipulated landscapes. We used a binary classification for lek type by assigning man-made leks a 1 and natural leks a 0. We included lek size as a numerical variable because accurate LPC counts were possible when flying over a lek to mark it. Following McRoberts et al. (2011*a*), we included a standardized survey date among our covariates by assigning our earliest survey date, 2 March, a value of 0 and consecutively numbering the following survey dates. Because lek attendance peaks in the middle of the spring (Haukos and Smith 1999) and the birds are less likely to flush during this period, we modeled a quadratic relationship for standardized date (McRoberts et al. 2011*b*).

For the all-detections dataset, our covariates included lek confirmation, detection type, and survey date. We included lek confirmation and detection type as categorical covariates and also included a standardized survey date with a quadratic term. Detections that were confirmed leks were assigned a 1 and non-lek detections were assigned a 0. For detection type, detections observed in a manipulated landscape (e.g., oil pad, grain field, or next to a stock tank) were assigned a 1 and detections observed in a natural landscape (e.g., grassland or shrubland) were assigned a 0. For this dataset, we regressed natural log transformed group size against our detection probability to correct for size-biased detection if $P < 0.15$ (Buckland et al. 2001).

We examined several key function and series expansion combinations as recommended by Buckland et al. (2001) to determine which model(s) best described detectability. These models included combinations of the half-normal, hazard rate, and uniform key functions and the cosine, hermite polynomial, and simple polynomial adjustment terms (Table 2.2). We model averaged among our competing models ($\Delta AIC_c \leq 2$) to account for model selection uncertainty (Burnham and Anderson 2002, Anderson 2008). We tested for differences in lek and LPC density estimates between strata with a *z*-test in program R (Buckland et al. 2001).

Results

We inventoried 105 survey blocks (90 from an R-22 and 15 from an R-44 helicopter) during 17 March through 3 June 2010 and surveyed 103 survey blocks (92 from an R-22 and 11 from an R-44 helicopter) during 1 March through 4 May 2011. In spring 2010 (northeast region), we flew 233.7 hr (2.2 hr/block) at an average speed of 63.3 km/hr (SE = 0.679) and in spring 2011 (southwest region), we flew 241.3 hr (2.3 hr/block) at an average speed of 60.8 km/hr (SE = 0.388). We surveyed a total distance of 13,403.4 km in the northeast and 13,407.5 km in the southwest and covered 88.6% of our sampling frame and 61.6% of the Texas LPC occupied range. We detected LPCs within 160.5 m of transect in the northeast and 178.3 m in the southwest.

We detected 66 LPC groups in the northeast; 35 were confirmed as leks, 10 were known leks, 1 detection was outside of the current LPC range in Texas, and 13 detections were within a CREZ. In the southwest, we detected 109 LPC groups; 61 were confirmed as leks, 15 were known leks, 4 detections were outside of the current LPC range, and 10 detections were within a CREZ. The average number of LPCs observed attending leks was 4.5 (SE = 0.670) and 5.2 (SE = 0.525) LPCs in the northeast and southwest, respectively.

We did not detect a difference in average encounter rate between strata and region for the leks-only dataset ($F_{3,\,200} = 1.008$, $P = 0.390$) and we also did not detect differences between strata and region for average cluster size and average encounter rates for the all-detections dataset ($F_{2,\,168} = 0.295$, $P = 0.745$; $F_{3,\,200} = 0.794$, $P = 0.499$, respectively). Therefore, we did not post-stratify the analysis by region for either dataset.

We found 1 model that was competitive for the leks-only dataset, the half-normal key function with lek size and lek type included as covariates (AIC$_c$ weight [w_i] = 0.235; Table 2.2). Detectability was greater for natural leks and larger lek sizes (Fig. 2.3). We found 2 competitive, parsimonious models for the all-detections dataset, the half-normal key function and cosine adjustment term (w_i = 0.211) and the hazard rate key function with no adjustment (w_i = 0.203; Table 2.3). Our lek and LPC density estimates for our sampling frame were 2.0 leks/100 km² (90% CI = 1.4–2.7 leks/100 km²) and 12.3 LPCs/100 km² (90% CI = 8.5–17.9 LPCs/100 km²), respectively (Table 2.4). We estimated 1.0 leks/100 km² (90% CI = 0.6–1.7 leks/100 km²) for the first stratum and 2.4 leks/100 km² (90% CI = 1.5–3.8 leks/100 km²), 2.7 leks/100 km² (90% CI = 1.6–4.3 leks/100 km²), and 2.7 leks/100 km² (90% CI = 1.3–5.7 leks/100 km²) for the second, third, and fourth strata, respectively. Our lek and LPC abundance estimates for our sampling frame were 293.6 leks (90% CI = 213.9–403.0 leks) and 1,822.4 LPCs (90% CI = 1,253.7–2,649.1 LPCs). Our LPC estimates include males and females because both genders were included in counts of individual birds for detections and hens not detected at leks were accounted for with our estimated detection function.

We detected a difference in lek density between strata 1 and 2 (Z = –1.972, P = 0.024), strata 1 and 3 (Z = –1.951, P = 0.026), and strata 1 and 4 (Z = –1.293, P = 0.098). We also detected a difference in LPC density between strata 1 and 2 (Z = –1.775, P = 0.038) and strata 1 and 3 (Z = –1.677, P = 0.047). We did not detect a difference in lek density between strata 2 and 3 (Z = –0.236, P = 0.407), strata 2 and 4 (Z = –0.197, P = 0.422), or strata 3 and 4 (Z = –0.030, P = 0.488). We also did not detect a difference in

LPC density between strata 1 and 4 ($Z = -1.193$, $P = 0.116$), strata 2 and 3 ($Z = -0.425$, $P = 0.335$), strata 2 and 4 ($Z = -0.142$, $P = 0.444$), or strata 3 and 4 ($Z = 0.197$, $P = 0.578$).

Discussion

We conducted the first randomized line-transect–based distance sampling survey of the LPC range in Texas to provide estimates of lek density. Overall, we detected 71 new leks, 25 known leks, 5 LPC observations outside the occupied state range, and 23 observations within 1 of the 2 CREZs. These new leks probably would not have been detected by traditional road-based lek surveys that many wildlife managers and biologists have implemented in the past (Butler et al. 2010, McRoberts et al. 2011*a*). We were also able to provide estimates of precision for our density estimates, which many previous population monitoring efforts have not done (Applegate 2000, McRoberts et al. 2011*a*).

Our model with the most support for leks only included all covariates (Table 2.2). However, the covariate "date" was ≤2 ΔAIC_c units of the second-highest ranked model. Because the penalty for including an additional parameter is 2 AIC_c units, it was most likely an uninformative parameter that did not explain enough variation to include it in a competitive model (Arnold 2010). McRoberts et al. (2011*a*) similarly found that date played a small role in lek detectability and concluded that an increase in lek detectability with date may have been due to observers developing a search image for leks. Lek size and lek type were the most influential covariates on lek detectability (Table 2.2). McRoberts et al. (2011*a*) also observed an increase in lek detectability with lek size, but they observed a higher detection probability for man-made leks and detected more of them. Our lek detectability was greater for natural leks, but mostly evident at small lek sizes (Fig. 2.3). It seems intuitive that displaying LPCs would be easier to spot on manipulated landscapes void of vegetation, such as abandoned oil pads, and that windmills or stock tanks would provide a visual cue for observers looking for leks (McRoberts et al. 2011*a*). However, Schroeder et al. (1992) concluded that lek detectability could be negatively influenced by landscape features that distract observers. Two GPC leks that were undetected on their helicopter surveys were located near a powerline or windmill.

Our detection probability for leks was lower than Schroeder et al. (1992) and McRoberts et al. (2011*a*) reported (51.0% compared to 67% and 72.3%, respectively) from their helicopter surveys. One possible explanation for our lower detection rate is our survey sampled the entire occupied range in Texas but Schroeder et al. (1992) and McRoberts et al. (2011*a*) surveyed high-density areas with known active leks. Of the 22 counties we surveyed, we only observed LPCs in 12 counties. We also flew more surveys outside the peak lekking period in order to complete our sampling effort. Lastly, our average lek sizes were smaller than those observed by Schroeder et al. (1992) (5.0 LPCs compared to 6.7 LPCs) and smaller leks are less detectable than large leks.

The abundance and density estimates from the literature differ from our estimates due to the techniques used to survey and estimate LPC density. We accounted for incomplete detectability of individuals within our sampling frame and provided probabilistic sampling of potential habitat. In contrast, other abundance and density estimates are derived from convenience-based sampling of higher-quality habitat that do not account for undetected individuals within the sampling frame, such as hens not attending leks (e.g., Davis et al. 2008). For example, Olawsky and Smith (1991) estimated summer and winter LPC densities in the southwest Texas Panhandle and southeastern New Mexico that were >150 times more than our LPC density estimates. They used a line-transect procedure to estimate lek density within their sampling frame, but transects were restricted to roads and their surveys were conducted in some of the highest-quality LPC habitat. Davis et al. (2008) estimated a Texas LPC abundance estimate of 15,730 LPCs (range = 6,077–24,132 LPCs), but LPC density was assumed constant across the entire range for the state and their study areas were some of the best habitat in the state. In contrast, Hamilton and Manzer (2011) used a modified point count design with distance sampling to estimate sharp-tailed grouse (*T. phasianellus*) lek density in east-central Alberta, and their regional density estimate was comparable to ours (2.6 leks/100 km^2; 95% CI=1.6–4.3 leks/100km^2).

We did not observe differences in average encounter rate between the northeast and the southwest regions, even though the regions represent 2 separate LPC populations (Taylor and Guthery 1980, Corman 2011). Historically, the northeastern populations have remained more stable than the southwestern populations and have experienced fewer declines in the number of males at leks (Sullivan et al. 2000). However, we detected almost twice as many leks in the southwest region. One possible explanation for this could be the increased density of oil and gas drilling in the northeast region during the past 20 years (Corman 2011). Another explanation is more agriculture production in the southwest region (USDA 2008) and thus, more sources of water and food. LPCs have been documented to use stock tanks for water, especially during a drought (Crawford and Bolen 1973, Pirius 2011) and LPCs may also use grain fields when there is less available food (Applegate and Riley 1998). Lastly, there is greater range overlap in Texas with increasing New Mexico LPC populations compared to decreasing Oklahoma populations (Davis et al. 2008). Therefore, LPC populations in the southwest region could be greater due to dispersing LPCs from populations in New Mexico (Corman 2011).

We observed a difference in lek density between strata 1 and 2, strata 1 and 3, and strata 1 and 4 and a difference in LPC density between strata 1 and 2 and strata 1 and 3. We anticipated having higher density estimates in strata 1 and 2 because LPCs primarily use native and CRP grasslands for breeding, nesting, and brood-rearing (Taylor and Guthery 1980, Applegate and Riley 1998); therefore we allocated less survey effort to blocks in strata 3 and 4. However, our greatest density estimates were in strata 3 and 4 while our lowest density estimate was for stratum 1 in the 2 CREZs (Table 2.4). We did not observe a difference in lek or LPC density between strata 2 and 3 or strata 2 and 4; however our results suggest that low-growing shrubs and a source of grain are important components of LPC habitat in Texas, given that stratum 3 was composed of ≥50% shrubland and stratum 4 was composed of a mix of grassland, shrubland, and grain fields. Other studies have reached a similar conclusion. For example, Patten et al. (2005) observed radio-marked LPCs in a survival study in southeastern New Mexico and northwestern Oklahoma occupying sites with a greater density of shrubs and having a higher survival rate for sites with >20% shrub cover. Percent of the landscape composed of shrubland patches (i.e., patches composed of shrubs <5 m tall comprising ≥20% of the total vegetation) was included in the best spatially-explicit model predicting lek density in Texas (AIC = 938.926, w_i = 0.826) and lek density peaked where landscapes were composed of ≈50% shrubland patches (Timmer 2012). Crawford and Bolen (1976) found the greatest lek density and populations in the southwest Texas Panhandle on sites with limited cultivation (e.g., 5–37%) as compared to sites with no or extensive cultivation.

The potential threats to declining prairie grouse populations require more effective population monitoring, such as aerial lek surveys. There are several ways to improve lek detectability from aerial surveys, as identified by McRoberts et al. (2011*a*), such as using helicopters instead of fixed-winged aircraft and restricting surveys to clear sunny mornings when visibility of LPCs is greatest. We further suggest not flying on windy mornings (e.g., wind speed >32 km/hr) as it is more difficult to control aircraft speed along transect and navigating turns over tall structures is more dangerous. Schroeder et al. (1992) observed a decrease in lek detection with an increase in helicopter speed, so flying transects at ≤60 km/hr should increase detection rate. McRoberts et al. (2011*a*) further recommended flying surveys during the peak lekking season when hen lek attendance is greatest and displaying and fighting males are most visible to observers. Disturbance to LPC breeding activity is also minimal during this period because the males are less likely to flush when hens are present at leks (McRoberts et al. 2011*b*). We observed LPCs flushing more frequently later in the morning in response to the helicopter, so restricting surveys to ≈2.5 hr post-sunrise should minimize this disturbance response.

If distance sampling and aerial surveys are used to estimate lek density, we recommend a few precautions to ensure quality data and accurate estimates. Critical assumptions must be met, such as complete detectability on the transect (Buckland et al. 2001), which is not possible with a fixed-winged aircraft. It is important to mark where the birds flushed from and the direction and distance that the birds flushed to avoid re-counting (Buckland et al. 2001). To prevent spiking of data at the center line (e.g., distances are erroneously allocated to on or just off the transect), pilots need to stay on the transect line until the helicopter is perpendicular to the detected lek rather than flying towards the lek to mark it when it is spotted in front of the helicopter. Observers can use rangefinders to measure distances to detections and clinometers to measure sighting angles, so distances can be estimated with basic trigonometry (Buckland et al. 2001). However, we found that deviating from the flight transect to a detection was more effective for obtaining an accurate location of a lek and it also provided a count of LPCs at each detection. The distance data should be examined while the data are being collected so problems, such as heaping, spiking, movement prior to detection, or missing animals on transect, can be corrected in the beginning of a field season (Buckland et al. 2001, Thomas et al. 2010). Finally, we included covariates that could have affected lek detectability, such as lek size, in order to improve precision of our density estimates (Marques et al. 2007).

Management Implications

Species of conservation concern, such as LPCs, require effective monitoring and management efforts. Aerial lek surveys can provide wildlife managers and biologists with accurate density and abundance estimates and distribution information. For example, the 2 CREZs in the Texas Panhandle overlap low-density portions of the LPC range, but overall LPC abundance in Texas is lower than previously thought. Wind energy developers and biologists can utilize our techniques to identify and monitor LPC populations that occur in potential wind resource areas. They can also avoid energy development in high-density portions of the LPC range. Our study provides an initial encounter rate and detection probability that can be used to determine the required transect length and expected number of detections, given a desired level of precision (Buckland et al. 2001). The amount of transects needed for a desired level of precision or expected number of detections may determine if aerial lek surveys are even a feasible and cost-effective management tool.

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Literature Cited

American Wind Energy Association. 2012. U.S. Wind Industry: fourth quarter 2011 market report. American Wind Energy Association, Washington, D.C., USA.

Anderson, D. R. 2008. Model based inference in the life sciences. Springer, New York, New York, USA.

Anderson, D. R. 2001. The need to get the basics right in wildlife field studies. Wildlife Society Bulletin 29:1294−1297.

Applegate, R. D., and T. Z. Riley. 1998. Lesser prairie-chicken management. Rangelands 20:13−15.

Applegate, R. D. 2000. Use and misuse of prairie chicken lek surveys. Wildlife Society Bulletin 28:457−458.

Arnold, T. W. 2010. Uninformative parameters and model selection using Akaike's Information Criterion. Journal of Wildlife Management 74:1175–1178.

Buckland, S. T., D. R. Anderson, K. P. Burnham, J. L. Laake, D. L. Borchers, and L. Thomas. 2001. Introduction to distance sampling: estimating abundance of biological populations. Oxford University Press, New York, New York, USA.

Burnham, K. P., and D. R. Anderson. 2002. Model selection and multimodel inference: a practical information-theoretic approach. Second edition. Springer, New York, New York, USA.

Butler, M. J., W. B. Ballard, M. C. Wallace, S. J. DeMaso, and B. K. McGee. 2007. Aerial surveys for estimating wild turkey abundance in the Texas Rolling Plains. Journal of Wildlife Management 71:1639–1645.

Butler, M. J., W. B. Ballard, M. C. Wallace, and S. J. DeMaso. 2008. Wild turkey (*Meleagris gallopavo*) detectability from helicopters and ramifications for estimating abundance. European Journal of Wildlife Research 54:148–152.

Butler, M. J., W. B. Ballard, R. D. Holt, and H. A. Whitlaw. 2010. Sound intensity of booming in lesser prairie-chickens. Journal of Wildlife Management 74:1160–1162.

Corman, K. S. 2011. Conservation and landscape genetics of Texas lesser prairie-chicken: population structure and differentiation, genetic variability, and effective size. Thesis, Texas A&M University-Kingsville, Kingsville, USA.

Crawford, J. A., and E. G. Bolen. 1976. Effects of land use on lesser prairie chickens in Texas. Journal of Wildlife Management 40:96−104.

Crawford, J. A., and E. G. Bolen. 1973. Spring use of stock ponds by lesser prairie chickens. The Wilson Bulletin 85:471–472.

Davis, D. M., R. E. Horton, E. A. Odell, R. D. Rogers, and H. A. Whitlaw. 2008. Lesser prairie-chicken conservation initiative. Lesser prairie chicken interstate working group. Unpublished Report. Colorado Division of Wildlife, Fort Collins, USA.

Electric Reliability Council of Texas. 2006. Analysis of transmission alternatives for Competitive Renewable Energy Zones in Texas. Electric Reliability Council of Texas, Austin, Texas, USA.

Hagen, C. A., B. E. Jamison, K. M. Giesen, and T. Z. Riley. 2004. Guidelines for managing lesser prairie-chicken populations and their habitats. Wildlife Society Bulletin 32:69−82.

Hamilton, S. and D. Manzer. 2011. Estimating lek occurrence and density for sharp-tailed grouse. Pages 31–49 *in* B. K. Sandercock, K. Martin, and G. Segelbacher, editors. Ecology, conservation, and management of grouse. Studies in Avian Biology, University of California Press, Berkeley, California, USA.

Haukos, D. A., and L. M. Smith. 1999. Effects of lek age on age structure and attendance of lesser prairie chickens (*Tympanuchus pallidicinctus*). American Midland Naturalist 142:415–420.

Hiby, L., and M. B. Krishna. 2001. Line transect sampling from a curving path. Biometrics 57:727–731.

Kuvlesky, W. P., L. A. Brennan, M. L. Morrison, K. K. Boydston, B. M. Ballard, and F. C. Bryant. 2007. Wind energy development and conservation: challenges and opportunities. Journal of Wildlife Management 71:2487−2498.

McRoberts, J. T., M. J. Butler, W. B. Ballard, H. A. Whitlaw, D. A. Haukos, and M. C. Wallace. 2011*a*. Detectability of lesser prairie-chicken leks: a comparison of surveys from aircraft. Journal of Wildlife Management 75:771−778.

McRoberts, J. T., M. J. Butler, W. B. Ballard, M. C. Wallace, H. A. Whitlaw, D. A. Haukos. 2011*b*. Response of lesser prairie-chickens on leks to aerial surveys. Wildlife Society Bulletin 35:27–31.

Marques, T. A., L. Thomas, S. G. fancy, and S. T. Buckland. 2007. Improving estimates of bird density using multiple-covariate distance sampling. Auk 124:1229–1243.

Olawsky, C. D., and L. M. Smith. 1991. Lesser prairie-chicken densities on tebuthiuron-treated and untreated sand shinnery oak rangelands. Journal of Range Management 44:364–368.

Patten, M. A., D. H. Wolfe, E. Shochat, and S. K. Sherrod. 2005. Effects of microhabitat and microclimate selection on adult survivorship of the lesser prairie-chicken. Journal of Wildlife Management 69:1270–1278.

Pirius, Nick. 2011. The non-breeding season ecology of lesser prairie-chickens (*Tympanuchus pallidicinctus*) in the Southern High Plains of Texas. Thesis, Texas Tech University, Lubbock, USA.

PRISM Climate Group. 2011. PRISM climate group, Oregon State University. <www.prism.oregonstate.edu>. Accessed 4 September 2011.

R Development Core Team. 2011. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. <www.R-project.org>. Accessed 12 June 2011.

Rusk, J. P., F. Hernandez, J. A. Arredondo, F. Hernandez, F. C. Bryant, D. G. Hewitt, E. J. Redeker, L. A. Brennan, and R. L. Bingham. 2007. An evaluation of survey methods for estimating Northern bobwhite abundance in Southern Texas. Journal of Wildlife Management 71:1336−1343.

Schroeder, M.A., K.M. Giesen, and C.E. Braun. 1992. Use of helicopters for estimating numbers of greater and lesser prairie-chicken leks in eastern Colorado. Wildlife Society Bulletin 20:106–113.

Sullivan, R. M., J. P. Hughes, and J. E. Lionberger. 2000. Review of the historical and present status of the lesser prairie-chicken (*Tympanuchus pallidicinctus*) in Texas. The Prairie Naturalist 32:177−188.

Taylor, M. A., and F. S. Guthery. 1980. Status, ecology, and management of the lesser prairie chicken. General Technical Report RM−77, U.S. Department of Agriculture, Forest Service, Rocky Mountain Forest and Range Experimental Station, Fort Collins, Colorado, USA.

Thomas, L., S. T. Buckland, E. A. Rexstad, J. L. Laake, S. Strindberg, S. L. Hedley, J. R. B. Bishop, T. A. Marques, and K. P. Burnham. 2010. Distance software: design and analysis of distance sampling surveys for estimating population size. Journal of Applied Ecology 47:5–14.

Thompson, W. L., G. C. White, and C. Gowan. 1998. Monitoring vertebrate populations. Academic Press, San Diego, California, USA.

Timmer, J. M. 2012. Spatially-explicit modeling of lesser prairie-chicken lek density in Texas, Chapter III Thesis, Texas Tech University, Lubbock, USA.

U. S. Department of Agriculture (USDA). 2008. USDA, National Agricultural Statistics Service (NASS), 2008 Texas Cropland Data Layer. 2008 edition. USDA, NASS Marketing and Information Services Office, Washington, D.C.

U.S. Fish and Wildlife Service. 2008. Candidate status review. Federal Register 73:75179−75180.

U.S. Fish and Wildlife Service. 1983. Endangered and threatened species listing and recovery priority guidelines. Federal Register 48:48098–48105.

U.S. Fish and Wildlife Service. 1998. Endangered and threatened wildlife and plants; 12-month finding for a petition to list the lesser prairie-chicken as threatened and designate critical habitat. Federal Register 63:31400–31406.

Walsh, D. P., G. C. White, T. E. Remington, and D. C. Bowden. 2004. Evaluation of the lek-count index for greater sage-grouse. Wildlife Society Bulletin 32:56−68.

Table 2.1. Sampling stratification and survey effort allocation for lesser prairie-chicken lek surveys in Texas during spring 2010 and 2011.

Stratum[a]	CREZ[b]	Landcover Type	Weighting Factor[c] (g_i)	Allocation of Survey Blocks[d]	Number of Blocks Surveyed/Total Available Blocks[e]
Priority 1	Yes	≥50% Grassland	0.4	72	76/97
Priority 2	No	≥50% Grassland	0.3	54	73/125
Priority 3	No	>50% Shrubland	0.2	36	39/39
Priority 4	Either	≥75% Grassland/ shrubland/grain field mix	0.1	18	20/24

[a] Lower numbers are a greater priority.

[b] Competitive Renewable Energy Zone.

[c] Weighting factor is calculated as $g_i = \frac{r_i}{\sum r_i}$.

[d] N = 180 blocks for 2010 and 2011.

[e] N = 208 blocks for 2010 and 2011; more blocks were available to survey in Priority 2 stratum than in Priority 1 stratum.

Table 2.2. Ranked models of lek density estimates from lesser prairie-chicken aerial surveys in Texas in spring 2010 and 2011 (n = 96 confirmed leks). For each candidate model, we give –2×log-likelihood (–2LL), number of parameters (K), second-order Akaike's Information Criterion (AIC_c), difference in AIC_c compared to lowest AIC_c of the model set (Δ_i), AIC_c weight (w_i), value of the probability density function of perpendicular distances at 0 m ($f(0)$), detection probability (P), and coefficient of variation for detection probability (cv(P)).

Model[a]	–2LL	K	AIC_c	Δ_i	w_i	$f(0)$	P	cv(P)
Half-normal (size+type+date)	304.568	5	315.235	0.000	0.403	0.012	0.482	0.109
Half-normal (size+type)	310.057	3	316.318	1.083	0.234	0.011	0.510	0.099
Half-normal (size)	313.266	2	317.395	2.160	0.137	0.011	0.532	0.097
Half-normal (size+date)	309.441	4	317.880	2.645	0.107	0.011	0.505	0.107
Hazard-rate (size)	312.399	3	318.660	3.425	0.073	0.016	0.355	0.135
Hazard-rate (size+type)	311.657	4	320.096	4.861	0.035	0.012	0.468	0.103
Hazard-rate (size+type+date)	310.423	6	323.367	8.132	0.007	0.013	0.446	0.113
Hazard-rate	323.773	2	327.902	12.667	0.002	0.016	0.355	0.452

Table 2.2. Continued

Model [a]	–2LL	K	AIC_c	Δ_i	w_i	$f(0)$	P	cv(P)
Half-normal + cosine	323.858	2	327.987	12.752	0.001	0.013	0.437	0.119
Uniform + cosine	322.585	3	328.845	13.610	<0.000	0.013	0.416	0.123
Hazard-rate (type)	325.492	3	331.753	16.518	<0.000	0.012	0.481	0.087
Hazard-rate (size+date)	321.778	5	332.444	17.209	<0.000	0.012	0.471	0.086
Hazard-rate (date)	325.380	4	333.820	18.585	<0.000	0.012	0.467	0.103
Half-normal (date)	328.476	3	334.737	19.502	<0.000	0.010	0.578	0.073
Half-normal (type+date)	326.415	4	334.854	19.619	<0.000	0.010	0.570	0.076
Half-normal (type)	331.052	2	335.181	19.946	<0.000	0.010	0.587	0.068
Hazard-rate (type+date)	324.728	5	335.394	20.159	<0.000	0.012	0.460	0.099

[a] Covariates include: size = size of lek, type = lek type (man-made or natural), date = quadratic function of standardized survey date.

Table 2.3. Ranked models of density estimates from lesser prairie-chicken aerial surveys in Texas in spring 2010 and 2011 (n = 175 detections). For each candidate model, we give –2×log-likelihood (–2LL), number of parameters (K), second-order Akaike's Information Criterion (AIC_c), difference in AIC_c compared to lowest AIC_c of the model set (Δ_i), AIC_c weight (w_i), value of the probability density function of perpendicular distances at 0 m ($f(0)$), detection probability (P), and coefficient of variation for detection probability (cv(P)).

Model[a]	–2LL	K	AIC_c	Δ_i	w_i	$f(0)$	P	cv(P)
Hazard-rate (lek)	562.443	3	568.584	0.000	0.256	0.016	0.354	0.102
Half-normal + cosine	564.894	2	568.964	0.380	0.211	0.015	0.379	0.078
Hazard-rate	564.977	2	569.047	0.463	0.203	0.016	0.350	0.210
Hazard-rate (lek+type)	561.302	4	569.537	0.954	0.159	0.016	0.342	0.094
Uniform + cosine	564.705	3	570.845	2.261	0.083	0.015	0.375	0.081
Hazard-rate (lek+day)	562.713	5	573.068	4.484	0.027	0.013	0.426	0.064
Hazard-rate (lek+type+day)	560.939	6	573.439	4.855	0.023	0.013	0.421	0.065

Table 2.3. Continued

Model[a]	–2LL	K	AIC_c	Δ_I	w_i	$f(0)$	P	cv(P)
Hazard-rate (type)	567.383	3	573.523	4.940	0.022	0.013	0.439	0.059
Hazard-rate (date)	567.360	4	575.595	7.011	0.008	0.013	0.432	0.060
Half-normal (lek)	573.270	2	577.340	8.756	0.003	0.011	0.497	0.056
Hazard-rate (type+day)	567.395	5	577.750	9.166	0.003	0.013	0.437	0.060
Half-normal (lek+date)	570.647	4	578.882	10.299	0.001	0.011	0.492	0.057
Half-normal (lek+type)	573.079	3	579.219	10.635	0.001	0.011	0.496	0.056
Half-normal (lek+type+date)	569.966	5	580.321	11.737	0.001	0.011	0.490	0.057
Half-normal (date)	577.571	3	583.711	15.127	<0.001	0.011	0.503	0.055
Half-normal (type+date)	577.273	4	585.508	16.924	<0.001	0.011	0.503	0.055
Half-normal (type)	581.440	2	585.509	16.926	<0.001	0.011	0.510	0.053

[a] Covariates include: lek = detection is confirmed lek or not, type = detection was observed in natural or man-made landscape, date = quadratic function of standardized survey date.

Table 2.4. Density and abundance estimates and average encounter rate for 2 datasets from lesser prairie-chicken (LPC) aerial surveys in Texas in spring 2010 and 2011.

	Density			Encounter				Abundance	
Dataset	D[a]	*cv*(D)	CI[b]	n[c]	L[d]	n/L	*cv*(n/L)	N[e]	CI
Leks-Only									
Stratum[f]	1.0	0.34	0.6–1.7	18	9,923.8	0.002	0.32	49.9	29.2–85.4
Stratum 2[g]	2.4	0.28	1.5–3.8	41	9,288.5	0.004	0.26	156.6	99.8–245.5
Stratum 3[h]	2.7	0.31	1.6–4.3	25	5,161.5	0.005	0.29	53.6	32.8–87.7
Stratum 4[i]	2.7	0.48	1.3–5.7	12	2,437.0	0.005	0.47	33.5	15.9–70.8
State-wide[j]	2.0	0.19	1.4–2.7	96	26,810.8	0.004	0.41	293.6	213.9–403.0
All Detections[k]									
Stratum 1	7.0	0.34	4.1–12.0	37	9,923.8	0.004	0.29	352.6	205.5–604.8
Stratum 2	14.4	0.30	8.9–23.1	71	9,288.5	0.008	0.24	931.6	579.3–1,498.0
Stratum 3	17.1	0.36	9.6–30.5	47	5,161.5	0.009	0.32	346.2	194.1–617.6

Table 2.4. Continued

	Density			Encounter				Abundance	
Dataset	D [a]	*cv*(D)	CI [b]	n [c]	L [d]	n/L	*cv*(n/L)	N [e]	CI
Stratum 4	15.4	0.46	7.5–31.9	20	2,437.0	0.008	0.43	192.0	93.0–396.4
State-wide	12.3	0.23	8.5–17.9	175	26,810.8	0.007	0.36	1,822.4	1,253.7–2,649.1

[a] Density estimates (D) measured in leks/100 km² for the leks-only datasets and LPCs/100 km² for the all-detections datasets.

[b] Ninety percent confidence intervals for density and abundance estimates.

[c] Number of confirmed lek detections for the leks-only dataset and number of all observations for the all-detections dataset.

[d] Transect length in kilometers.

[e] Abundance estimates (N) measured in leks for the leks-only dataset and LPCs for the all-detections dataset.

[f] Stratum 1 includes survey blocks within a Competitive Renewable Energy Zone (CREZ) and composed of ≥50% grassland.

[g] Stratum 2 includes survey blocks not within a CREZ and composed of ≥50% grassland.

[h] Stratum 3 includes survey blocks not within a CREZ and composed of >50% shrubland.

[i] Stratum 4 includes survey blocks not within a CREZ and composed of ≥75% grassland/shrubland/grain field mix.

[j] Includes the estimated occupied LPC range for Texas.

[k] The half-normal + cosine and hazard-rate models were model-averaged for the LPC density and abundance estimates.

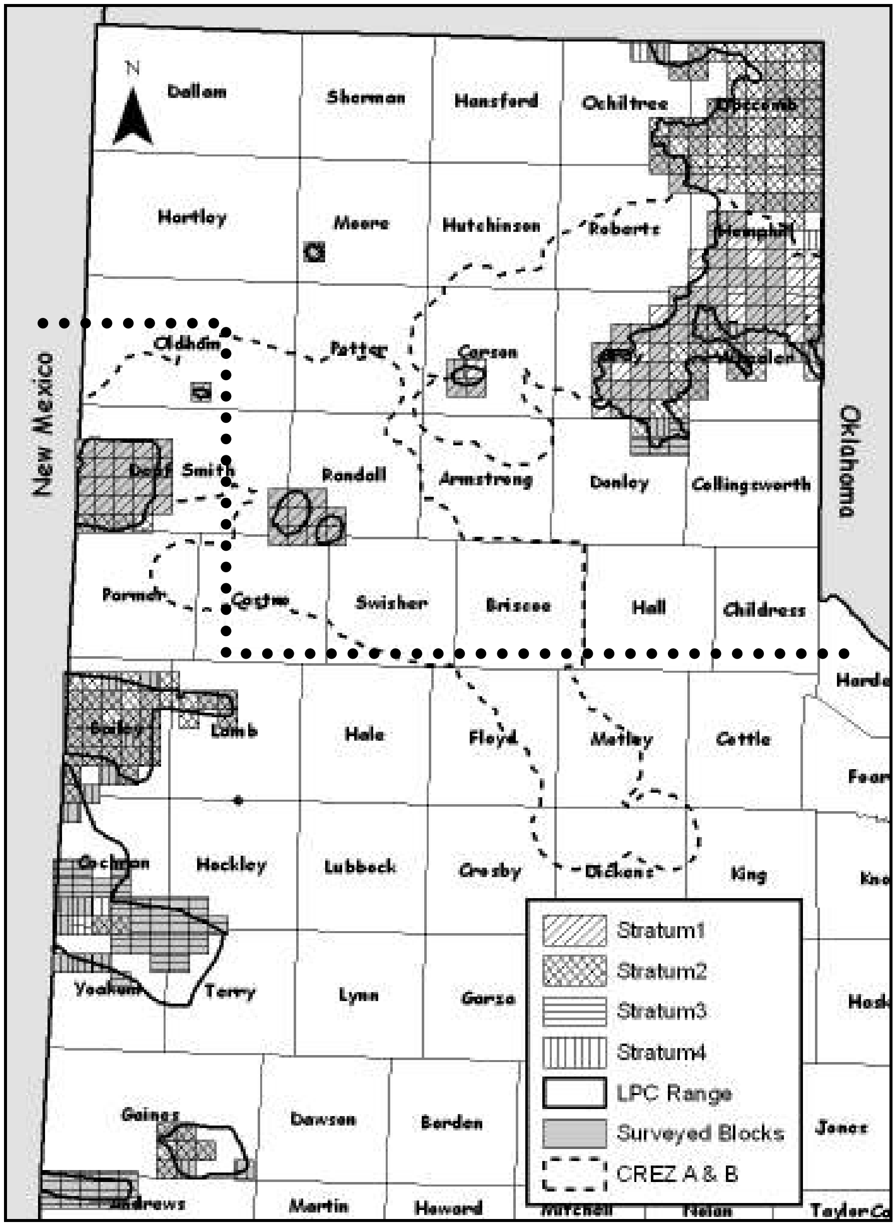
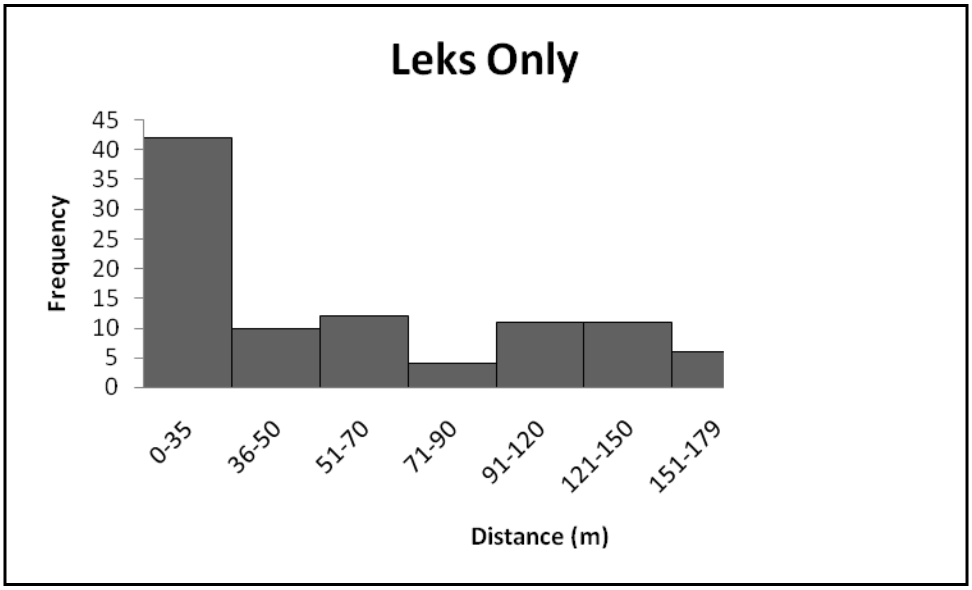


Figure 2.1. Lesser prairie-chicken (LPC) survey blocks in Texas for spring 2010 (northeast and central region) and 2011 (southwest and west-central region; separated by dotted line) with the estimated LPC range, 2 Competitive Renewable Energy Zones (CREZ), and 4 strata. Whites areas inside the occupied range were classified as non-LPC habitat and were not included in the sampling frame.



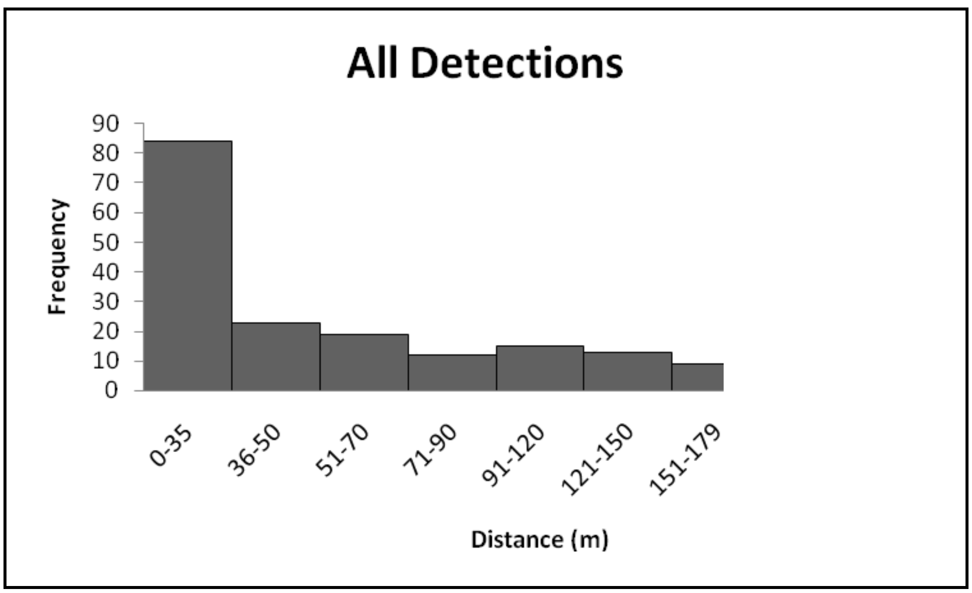


Figure 2.2. Grouped distance data for leks only (*n*=96) and all detections (*n*=175) during 2010 and 2011 lesser prairie-chicken aerial surveys in Texas.

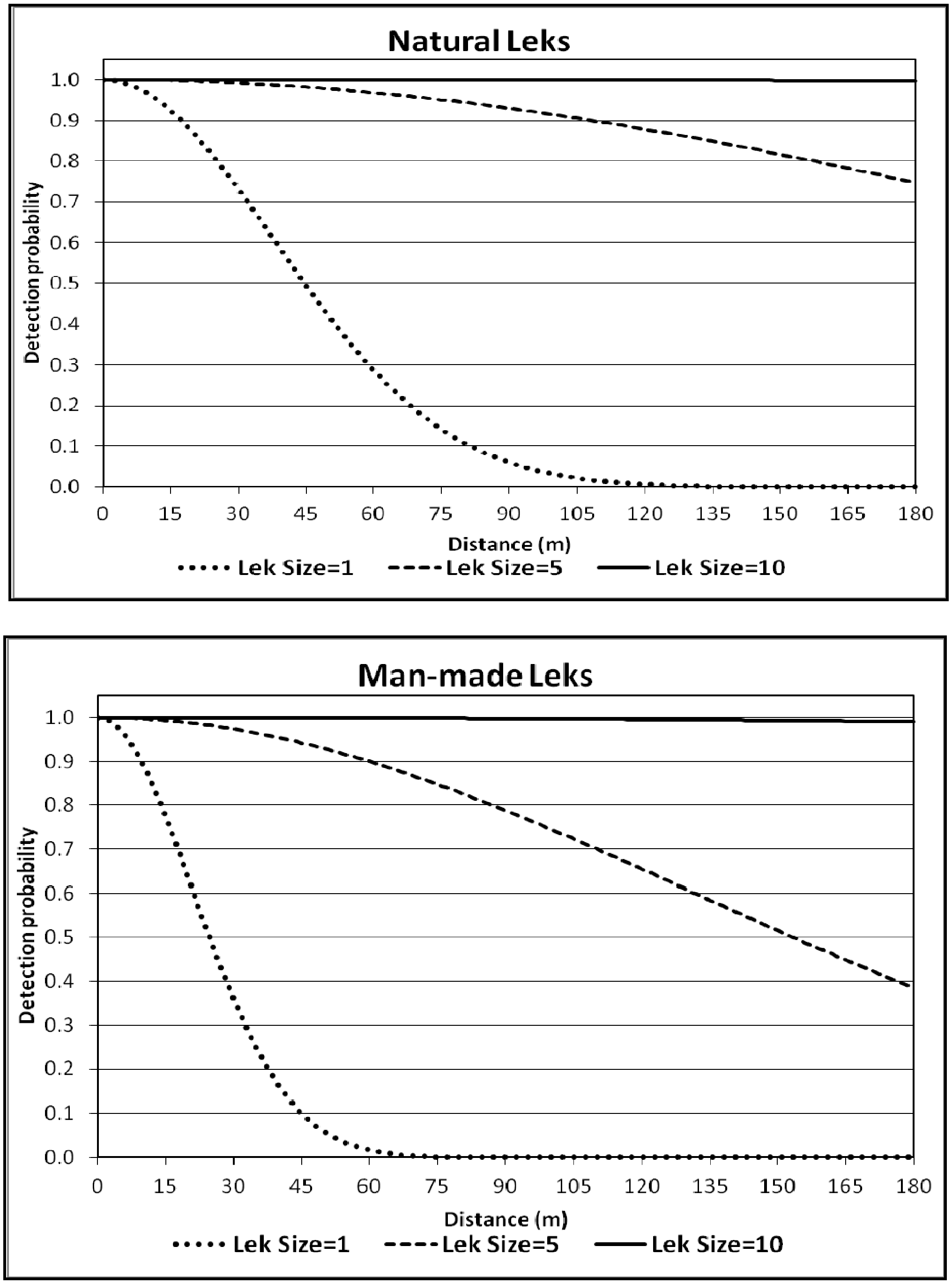


Figure 2.3. Predicted detectability for lesser prairie-chicken leks (n = 96) from 2010 and 2011 aerial surveys in the Texas occupied range.

CHAPTER 3

SPATIALLY-EXPLICIT MODELING OF LESSER PRAIRIE-CHICKEN LEK DENSITY IN TEXAS

Abstract

As with many other grassland birds, lesser prairie-chickens (LPC; *Tympanuchus pallidicinctus*) have experienced population declines in the Southern Great Plains and are a candidate species under the Endangered Species Act. Lesser prairie-chickens now face a new potential disturbance, wind energy. Texas currently produces the most wind power in the United States and west Texas in particular has been identified as a source for greater energy production. Therefore, we estimated lek abundance in the Texas occupied LPC range and modeled vegetative and anthropogenic landscape characteristics associated with lek density. To estimate the abundance of leks, we employed an aerial line-transect–based survey method to count LPC leks in spring 2010 and 2011. We surveyed 208 randomly-selected 5,184-ha blocks in 4 separate strata. Stratification was based on the greatest potential for wind energy development to impact LPC lek density. We then used hierarchical distance sampling to model the relationship between lek density and vegetative and anthropogenic features on the landscape. Our best model included percent of the landscape composed of shrubland patches (i.e., patches composed of shrubs <5 m tall comprising ≥20% of the total vegetation) + paved road density + unpaved road density (AIC = 938.926, w_i = 0.826). Lek density peaked where ≈50% of the landscape was composed of shrubland patches and was greatest at lower paved and

unpaved road densities. We estimated 248.5 leks (*cv* = 0.136) for our sampling frame. To promote greater LPC lek density in Texas, wildlife managers should strive to maintain landscapes composed of ≈50% shrubland patches and avoid increased road densities in regions with LPCs. Our spatially-explicit models can be used to predict how lek density may change in response to changes in habitat conditions and road densities.

Introduction

The occupied range of lesser prairie-chickens (LPC; *Tympanuchus pallidicinctus)* has been reduced by >90% and this loss has been attributed to direct habitat loss from conversion of native grassland to cropland, livestock overgrazing, and invasion of woody plants, and indirect habitat loss from disturbance by energy development (Taylor and Guthery 1980, Applegate and Riley 1998, Hagen et al. 2004). As a result, the LPC was petitioned for listing under the Endangered Species Act (ESA) as threatened or endangered in 1995 and in 1998 the U.S. Fish and Wildlife Service (USFWS) determined that listing was "warranted, but precluded" (USFWS 1998). The listing was recently upgraded from Priority 8 to Priority 2, and among the reasons were an "increased magnitude of threats" from oil and wind energy development (USFWS 2008).

An increased demand for renewable and non-renewable energy could impact prairie grouse species (*Tympanachus* and *Centrocercus* spp.) that inhabit native prairies and sagebrush steppe where there is high potential for wind, geothermal, and natural gas energy development (Hagen 2010, Jarnevich and Laubhan 2011, Naugle et al. 2011). As a result, several recent studies have examined impacts of energy development on prairie grouse and many of these studies demonstrate avoidance of anthropogenic structures and human disturbance that leads to habitat loss and fragmentation (Holloran 2005, Pitman et al. 2005, Walker et al. 2007, Doherty et al. 2008, Pruett et al. 2009). For example, Naugle et al. (2011) compiled 7 scientific studies to examine the impact of energy development on greater sage-grouse (GSG; *C. urophasianus*) in the Intermountain West. Every study reported consistent negative responses of GSG to energy development, such as a decrease in lek attendance within or near gas fields and an avoidance of development by nesting hens. Hagen (2010) conducted a meta-analysis of published and unpublished reports pertaining to prairie grouse and the impacts of energy development. He found a general displacement of grouse by anthropogenic features and reduced demographic rates from energy development.

Texas currently produces the most wind power in the United States (i.e., 22.0% of the nation's total; American Wind Energy Association 2012) and 5 Competitive Renewable Energy Zones (CREZ) were designated in west Texas to encourage further wind energy development (Electric Reliability Council of Texas [ERCOT] 2006). Transmission lines are already being constructed to deliver wind-produced electricity from these CREZs to customers in urban centers (ERCOT 2006). The 2 CREZs in the Texas Panhandle overlap approximately 27% (3,288 km^2) of the known occupied range of LPCs in Texas. Little is known about the current spatial distribution of LPC leks in the Texas range relative to features such as roads, transmission lines, and oil and gas development, and few peer-reviewed studies have investigated the potential impacts from wind facilities and associated infrastructure on prairie grouse (Kuvlesky et al. 2007).

Spatially-explicit models allow researchers to associate landscape and anthropogenic features with animal abundance or density (Hedley and Buckland 2004, Royle et al. 2004, Jarnevich and Laubhan 2011). Identifying suitable habitat and predicting species occurrence is especially useful when balancing energy development and the needs of species of conservation concern, such as LPCs (Jarnevich and Laubhan 2011). Niche-based models incorporate presence-only data and formulate statistical relationships between species occurrence and environmental characteristics (Jarnevich and Laubhan 2011), but these models of maximum entropy are susceptible to problems associated with biased samples (e.g., non-random samples; Elith et al. 2011, Royle et al. 2012). Further, they only estimate prevalence, which is a relative measure of occurrence, not the probability of presence (Elith et al. 2011, Royle et al. 2012). Hierarchical distance sampling models incorporate a detection function to estimate density and then relate landscape features to density (Royle et al. 2004); therefore, associations are not biased by incomplete detection of individuals.

Lesser prairie-chicken populations in Texas have faced steady declines during the past 100 years (Jackson and DeArment 1963, Crawford and Bolen 1976*a*, Sullivan et al. 2000) and Texas Parks and Wildlife Department (TPWD) estimated a minimum of 6,000 birds from mostly road-based surveys located in high quality LPC habitat (Davis et al. 2008). Given inevitable wind energy development in west Texas where declining LPC populations occur (ERCOT 2006), there is a need for a better understanding of lek density in relation to anthropogenic and vegetative landscape features. In addition, McRoberts et al. (2011) identified a need for more effective monitoring of LPC populations given their conservation status. Therefore, our objectives were to develop hierarchical distance sampling models of lek density relative to anthropogenic and vegetative landscape characteristics and estimate lek abundance in the Texas occupied range based on these models. We identified landscape covariates that influence lek density to help guide LPC conservation efforts and inform wind facility siting decisions.

Study Area

The current estimated range of LPCs in Texas lies mostly in the northeast and southwest portions of the Texas Panhandle, with a few birds thought to be scattered throughout the central portion (Davis et al. 2008). Our sampling frame encompassed 86.9% of the Texas occupied LPC range (i.e., we excluded portions that were not LPC habitat such as riparian woodlands and cotton fields), while focusing on the intersection of current LPC range and the 2 CREZs. The northeast region of the study area was comprised of a mixed-grass prairie dominated by sand sagebrush (*Artemisia filifolia*) and little bluestem (*Schizachyrium scoparium*). The southwest region of the study area was a short-grass prairie dominated by shinnery oak (*Quercus havardii*) and little bluestem with some mesquite (*Prosopis glandulosa*). Cotton, winter wheat, and grain sorghum were the main crops grown in the region (United States Department of Agriculture [USDA] 2008). The climate of the Panhandle was mostly dry and the majority of the precipitation occurred during the fall and spring (PRISM Climate Group 2011). The southwest region of the Panhandle received an average of 40−51 cm of precipitation yearly and the northeast region received an average of 50−61 cm of precipitation yearly (PRISM Climate Group 2011).

Methods

We used a stratified random sampling design with 4 strata (Thompson et al. 1998). The 4 strata were based on vegetative characteristics thought to influence LPC density (e.g., grassland, shrubland, agriculture, and a mosaic) and potential for wind energy development near LPC-occupied habitat. For example, areas composed mostly of native and Conservation Reserve Program (CRP) grasslands were grouped together into one stratum because LPCs use this habitat for breeding, nesting, and brood-rearing (Crawford and Bolen 1976*a*, Taylor and Guthery 1980, Hagen et al. 2004). We delineated vegetation types based on the USDA Texas cropland data layer (USDA 2008). The sampling frame was divided into 329, 7.2 km × 7.2 km surveys blocks. At this size, we could complete 1 survey block per flight.

The first stratum was composed of survey blocks that were within a CREZ and ≥50% grassland (patches were native grassland, CRP, or idle cropland comprising >80% of the total vegetation). The second stratum was composed of survey blocks that were also ≥50% grassland, but not within a CREZ. The third stratum was composed of survey blocks with >50% shrubland (i.e., patches composed of shrubs <5 m tall comprising ≥20% of the total vegetation) and this particular composition did not occur within a CREZ. The fourth stratum was composed of survey blocks with a ≥75% combination of grassland/shrubland/grain field (this mosaic was comprised of 30–50% grassland, ≤50%

shrubland, and >0% grain field) and 1 of these blocks was located within a CREZ. The specifications for this stratum were meant to include potential LPC habitat while excluding non-habitat, such as urban areas, water bodies, cotton fields, and woodland regions (e.g., riparian cottonwood [*Populus deltoides*] galleries).

We allocated sample size to each stratum using the following formula

$$u_i = U \times g_i$$

where u_i is the number of survey blocks allocated to each stratum i, U is the total number of survey blocks allocated for the 2-year study and g_i is the weighting factor for each stratum i. The weighting factor was calculated as

$$g_i = \frac{r_i}{\sum r_i}$$

where r_i was the rank for each stratum i. The strata were ranked from 1 to 4 with 4 representing the highest priority stratum. Because we were most interested in examining LPC density in areas subject to wind energy development, we prioritized the strata based on the greatest potential for wind energy development to impact lek distribution. We planned to survey 180 blocks over 2 survey years. Based on the weighting factors, we randomly-selected 72 survey blocks in the first stratum, 54 in the second stratum, 36 in the third stratum, and 18 in the fourth stratum. We selected some additional blocks from each stratum in case we were able to survey more blocks than planned.

We used ArcGIS 9.3 (Environmental Systems Research Institute, Inc., Redlands, CA) to create a set of grid cells (7.2 km × 7.2 km) over the extent of the occupied LPC range in Texas. We re-classified and grouped landcover based on the Texas cropland data layer (USDA 2008) into 8 categories (e.g., cotton, grains, other crops, grassland or idle pasture, shrubland, woodland, open water, and barren or developed areas) and calculated the area of grassland, shrubland, and grain in each survey block. We combined this information with the 2 CREZs in the Panhandle and assigned survey blocks to 1 of the 4 strata and then randomly-selected blocks from each stratum. Of the 329 survey blocks covering the sampling frame, we did not consider 44 blocks as potential LPC habitat because they were mostly urban, open water, cotton fields or woodland, and so were not included in any strata.

We used ArcGIS 9.3 to generate a flight path for each survey block and measure the nearest distance from each detection to a transect (Hiby and Krishna 2001). Transects were oriented north-south with 400-m spacing between them. The observer's global positioning system (GPS) unit recorded a track log of each flight path to provide the actual transect lengths that were surveyed. We set the track logs to record points at least every 2 seconds.

We divided our sampling frame into 2 regions for the 2 field seasons. During spring 2010, we surveyed blocks in the northeast and central regions of the Panhandle (hereafter, northeast region) and during spring 2011, we surveyed blocks in the southwest and west-central regions (hereafter, southwest region). We conducted our surveys from an R-22 helicopter (Robinson Helicopter Co., Torrance, CA), which seated the pilot and 1 observer. To train technicians, we also conducted flights early in each field season from an R-44 helicopter (Robinson Helicopter Co., Torrance, CA). We conducted flights between early-March and late-May 2010–2011. We followed the survey protocol developed by McRoberts et al. (2011) (i.e., target altitude of 15 m above ground-level, target speed of 60 km/hr, survey between sunrise until ≈2.5 hr post-sunrise). We did not include portions of transects that were surveyed outside the set survey protocol (e.g., when the pilot increased the helicopter's altitude to avoid towns or feedlots) in the final analyses. When LPCs were detected, the pilot deviated from transect and flew over the center of the group of birds or the center of the location from where birds flushed. We used a GPS unit to record the exact location of detected LPCs.

Data Analysis

We selected11 vegetative and anthropogenic covariates that could influence lek density based on previous literature and our research objectives (Copelin 1963, Crawford and Bolen 1976*a*, Taylor and Guthery 1980, Woodward et al. 2001, Fuhlendorf et al. 2002, Pruett et al. 2009; Table 3.1). We divided each survey block into 4, 12.96-km^2 quadrats and calculated landscape covariates for each quadrat. We developed 3 a priori model sets (Table 3.2). Our vegetation model set included percent grassland (i.e., composed of native grassland, CRP, or idle cropland and comprising >80% of the total vegetation in a patch), percent shrubland (i.e., shrubs <5 m tall and comprising ≥20% of the total vegetation in a patch), percent grain field (e.g., corn, winter wheat, or grain sorghum), average grassland patch size (km^2), average shrubland patch size (km^2), and edge density of all patches (km/km^2; Texas cropland data layer, USDA 2008). We also included a quadratic term with percent grassland and percent shrubland because previous literature has suggested that optimum LPC habitat consists of native grassland interspersed with some shrubland (Copelin 1963, Taylor and Guthery 1980, Applegate and Riley 1998). Our road model set included paved road density (km/km2), unpaved road density (km/km^2), and all road density (km/km^2; U.S. Environmental Protection Agency 1998, Texas Department of Transportation 2011). Our energy model set included density of transmission lines ≥69 kv (km/km^2; Platts 2011) and active oil and gas well density (wells/km^2; Railroad Commission of Texas 2011). We performed a correlation analysis in program R (R Development Core Team 2011) for the landscape covariates (Appendix A). We did not include variable(s) in the same model which had a pair-wise correlation ≥ 0.50 to avoid problems with multicollinearity (Ribic and Sample 2001).

We analyzed our data using the "distsamp" function of package "unmarked" (Fiske and Chandler 2011) in program R (Appendix B) which implements the multinomial-Poisson mixture model (hierarchical distance sampling; Royle et al. (2004). We binned our distance data into 7 intervals (e.g., 0–35 m, 35–50 m, 50–70 m, 70–90 m, 90–120 m, 120–150 m, 150–179 m) and used the half-normal model to describe the detection function. The 3 a priori model sets (vegetative covariates, road covariates, and energy infrastructure covariates) were used to model the lek density relationships (Table 3.2). For the vegetation model set, we did not allow percent grassland, percent shrubland, average grass patch size, or average shrub patch size to appear together in the same model to reduce the complexity and avoid multicollinearity among the covariates (Appendix A). For the road and energy model sets, we included models for each individual variable and the covariates combined (Table 3.2). However, for the model including all road density, we did not include either paved or unpaved road density to avoid multicollinearity. We determined competitive models as a model with ΔAIC ≤ 2 and excluded models with uninformative parameters (Arnold 2010). We considered the best models from each model set and combined those models in a final model set along with a null model (Table 3.3). We evaluated goodness-of-fit of the best model(s) using a Freeman-Tukey chi-squared procedure with 1000 bootstrap replicates ("parboot"; Fiske and Chandler 2011). We model averaged among our most competitive models to account for model selection uncertainty (Burnham and Anderson 2002) and provided robust inference and prediction. We created a lek density map in ArcGIS for each 12.96-km^2 quadrat covering the LPC range in Texas based on the model-averaged predictions. We estimated the total number of leks for our sampling frame and used the parametric procedure with 1,000 bootstrap replicates to estimate uncertainty in the lek abundance estimate ("parboot"; Fiske and Chandler 2011).

Results

During spring 2010 and 2011, we inventoried 208, 51.84-km^2 survey blocks across the estimated LPC range in Texas. We surveyed 88.6% of the sampling frame (10,782.7 of 12,167.1 km^2) which was 61.6% of the Texas LPC occupied range. We detected 96 leks.

We found 2 competitive models from our vegetation set: percent shrubland (AIC = 945.098, AIC weight [w_i] = 0.487) and percent shrubland + percent grain field (AIC = 946.558, w_i = 0.235; Table 3.2). There was a quadratic relationship between lek density and percent shrubland, in which lek density peaked when ≈50% of a quadrat was composed of shrubland patches (Fig. 3.1). The model containing percent grain field was ≤2 ΔAIC units of the top- ranked model and the parameter estimate did not differ from 0 for percent grain field (β = 0.689, SE = 0.917, P = 0.453); therefore, it was probably an uninformative parameter.

We found 2 competitive models from the road model set: paved road density + unpaved road density (AIC = 945.134, w_i = 0.716) and unpaved road density (AIC = 946.988, w_i = 0.284; Table 3.2). These 2 models were ≤2 ΔAIC units of each other; however both covariates were significant at α = 0.15 and therefore, both were informative (Arnold 2010). Unpaved road density was inversely related to lek density in the model with and without paved road density (β = –0.316, SE = 0.118, P = 0.008; β = –0.307, SE = 0.118, P = 0.010, respectively; Fig. 3.2) and paved road density was also inversely related to lek density (β = –1.228, SE = 0.641, P = 0.056).

We found 2 competitive models from the energy model set: transmission line density (AIC = 950.773, w_i = 0.636) and transmission line density + active oil and gas well density (AIC = 9552.558, w_i = 0.260; Table 3.2). However, the model that included active oil and gas well density was ≤2 ΔAIC units of the top- ranked model and the parameter estimate did not differ from 0 (β = 0.018, SE = 0.037, P = 0.633) indicating that model was likely spurious (Arnold 2010). The best model indicated an inverse relationship between lek density and transmission line density (β = –0.247, SE = 0.144, P = 0.086).

We combined our competitive models from each set (e.g., percent shrubland, paved road density + unpaved road density, unpaved road density, and transmission line density) and fit the final model set (Table 3.3). The most competitive model included percent shrubland + paved road density + unpaved road density (AIC= 938.926, w_i = 0.826; Table 3.3). Goodness of fit test indicated good model fit (χ^2 = 0.864; P = 0.477). Based on this model, we estimated 248.5 leks (cv = 0.136) in our sampling frame.

Discussion

We found that percent of the landscape composed of shrubland patches (i.e., shrubs <5 m tall comprising ≥20% of the total vegetation) was a significant predictor of lek density. Lek density peaked when ≈50% of the landscape was composed of shrubland patches (Fig. 3.1). Lesser prairie-chicken habitat guidelines often recommend large tracts of ≈80% native grassland and ≈20% shrubs to support LPC populations (e.g., Bidwell 2003). In Kansas, percent grassland or percent grassland and CRP were important predictors of LPC lek occurrence (Jarnevich and Laubhan 2011). However, low-growing shrubs are an important component of LPC habitat for nesting and brood cover, a seasonal source of insects and mast, and thermal cover (Applegate and Riley 1998, Pitman et al. 2005, Bell et al. 2010). Copelin (1963) described LPC habitat as a "low to high density shrub savannah" with shrubs <1 m tall. Applegate and Riley (1998) recommended a range of 30–45% shrub composition for nesting, brood-rearing, and fall and winter foraging. At a large scale, Woodward et al. (2001) found that declining LPC populations in New Mexico, Oklahoma, and Texas were associated with less shrub composition, and a greater rate in loss of shrubland. In addition, shrubs comprised 76.9% of the native vegetation of the landscapes in the study (Woodward et al. 2001). Radio-marked birds in a survival study in southeastern New Mexico and northwestern Oklahoma occupied sites with a greater density of shrubs and had a higher survival rate for sites with >20% shrub cover (Patten et al. 2005). Bell et al. (2010) similarly observed broods selecting for sites with greater shinnery oak canopy cover in southeast New Mexico.

The landcover type classified as "shrubland" in our study included low-growing shrubs and grasses (USDA 2008), whereas the landcover type classified as "grassland" may have been a monoculture of lower quality lacking the habitat heterogeneity and structure that LPCs require (Applegate and Riley 1998). Sullivan et al. (2000) noted that the 15,000 km^2 of CRP that were established in the Texas Panhandle in 1985 were comprised mostly of monoculture stands of non-native grasses. A heterogeneous environment of grasses, low-growing shrubs, and forbs is needed to support various LPC life stages, such as lekking, nesting, and brood-rearing (Taylor and Guthery 1980, Hagen et al. 2004, Fields et al. 2006). Timmer (2012) estimated the lowest lek density in Texas for a stratum composed of $\geq$50% grassland (0.99 leks/100 km^2, cv = 0.336), which provides support for this explanation. Further, Timmer (2012) estimated the highest lek density in Texas for the stratum composed of a mix of grassland, shrubland, and grain field (2.70 leks/100 km^2, cv = 0.480), followed by the stratum composed of >50% shrubland (2.65 leks/100 km^2, cv = 0.307). Given the high inverse correlation between percent shrubland and percent grassland in our study (r = –0.86), it is logical to assume that a landscape supporting a high lek density with ≈50% shrubland patch composition would contain ≈50% grassland patches. However, percent grassland was not included in any of our competitive models as a significant predictor of lek density.

Both paved road density and unpaved road density were included in our top model and both indicated an inverse relationship to lek density (Fig. 3.1); however paved road density had a stronger influence on lek density. Pruett et al. (2009) concluded that highways do not appear to impede LPC movement, but noise and traffic associated with highways may render surrounding habitat unsuitable. An avoidance of high road densities at a 5-km scale was a significant predictor of GPC lek locations in Kansas for hierarchical niche modeling (Gregory et al. 2011). Niche modeling of LPC lek locations in Kansas showed an increase in lek habitat quality with increasing distance from a highway (Jarnevich and Laubhan 2011), while a separate study in Kansas observed an avoidance of paved roads by radio-marked hens (Hagen et al. 2011). Lesser prairie-chicken nests in Kansas were also located further than expected from paved and high-traffic graveled roads even though otherwise-suitable habitat surrounded these features (Pitman et al. 2005). Distance to 2-track or ungraded service road was a significant predictor of nest success and 9 of 11 nests were located further from an unpaved road than randomly expected for 1 study site (Pitman et al. 2005). The authors speculated that this may have been due to predators traveling on the roads and preying on nests located near the roads.

An avoidance of unpaved roads could also be due to disturbance from agricultural or oil and gas traffic. For example, Crawford and Bolen (1976*b*) documented lek abandonment when a frequently-used road was built over a lek in native rangeland. In a natural gas field development region in western Wyoming, Holloran (2005) observed a decline in GSG lek attendance with increasing traffic volume on main haul roads and a decline in lek attendance for leks located within 3 km of a main haul road. In a separate study in northwestern Wyoming, GSG hens nested further from disturbed leks (i.e., leks within 3 km of a natural gas well pad or road) than undisturbed leks (Lyon and Anderson 2003). The authors attributed this behavior to an avoidance of vehicular traffic associated with the gas wells rather than the wells themselves. Several studies have documented an avoidance of prairie grouse to oil or gas wells (e.g., Pitman 2005, Walker et al. 2007, Doherty et al. 2008, Hagen et al. 2011), but the magnitude of activity associated with anthropogenic features, such as wells or roads, may be the reason for avoidance behavior rather than the actual feature. Indeed, lesser prairie-chickens will use oil or gas pads, 2-tracks, and gravel roads if the activity or traffic associated with these features is minimal (Crawford and Bolen 1976*b*, Jamison et al. 2002). Therefore, LPCs in Texas may be responding to the vehicular traffic associated with oil or gas activity rather than the actual oil or natural gas extraction given that well density was not a significant predictor of lek density in our study.

Transmission line density was not included in our top model, but it was a significant predictor of lek density and indicated an inverse relationship to lek density. Several other studies have also documented an avoidance of transmission lines by prairie grouse. In an Oklahoma study, radio-marked LPCs avoided a power line in the study area by ≥100 m and few nests were found within 2 km of the power line; radio-marked greater prairie-chickens (GPC; *T. cupido*) also appeared to avoid the power line in the study area (Pruett 2009). Hagen (2010) found that prairie grouse displacement by anthropogenic features in several studies was greatest for transmission lines and roads. Hagen et al. (2011) examined the influence of anthropogenic features, such as transmission lines, improved roads, and oil or gas wells, on LPC hen habitat use and observed that transmission lines were 1 of the most avoided anthropogenic features. Two separate studies in Kansas both documented avoidance of transmission lines and an increase in nesting or lek habitat quality with increasing distance from transmission line (Hagen et al. 2011, Jarnevich and Laubhan 2011). No study has examined the reason behind prairie grouse avoidance of tall structures, such as transmission lines, but 1 possible explanation for this avoidance may be that prairie chickens avoid the threat of predation from raptors perching on the structures (Pitman et al. 2005, Pruett et al. 2009).

Habitat fragmentation was 1 of the reasons LPCs were issued a higher-priority listing for the ESA (USFWS 2008). Fuhlendorf et al. (2002) found that habitat fragmentation, such as a reduction in the largest patch index and an increase in edge density were greatest for landscapes with declining LPC populations. Further, GPCs breeding in larger, continuous tracts of native prairie in eastern Kansas had higher annual survival than GPCs breeding in a fragmented prairie, which exhibited lower annual survival than ever reported (McNew et al. 2011). While edge density and average grassland and average shrubland patch size were not significant predictors of lek density in our study, paved and unpaved road densities and transmission line density were significant predictors. These linear features can fragment contiguous rangeland and result in habitat loss due to avoidance of these features by LPCs (Pruett et al. 2009, Hagen et al. 2011).

The hierarchical modeling technique we used is different than the techniques utilized in other studies examining lek density and landscape features. Therefore, different results can be expected. We set up a formal study to provide spatial coverage of our sampling frame and used probabilistic sampling for the Texas occupied LPC range. We accounted for incomplete detection of leks by modeling a detection function and were thus, able to extrapolate our relationship between lek abundance and predictive covariates to the entire LPC range in Texas (Buckland et al. 2001). In contrast, the niche models predicting lek occurrence in Kansas are not based on a formal statistical design which can introduce sampling biases (Jarnevich and Laubhan 2011, Gregory et al. 2011). For example, most lek locations used were sampled from roads only.

Our study is unique for prairie grouse and well-designed, but it highlights the need for similar modeling efforts of landscape features and lek density throughout the LPC range. Our best model may not accurately predict LPC lek density in Colorado, Kansas, New Mexico, or Oklahoma because the type and intensity of anthropogenic activity and its impact on LPCs may vary greatly in other portions of the LPC range. Further, grazing intensity, fire frequency, soil types, local weather, and a suite of other factors can cause structural and compositional differences in vegetation throughout the LPC range. A regional habitat-priority map for LPCs throughout their range that is based on accurate models of lek density and landscape features is currently lacking (Hagen 2010). A consistent and detailed landcover layer for the LPC range is also lacking and could improve modeling efforts. Additionally, modeling lek density with change in habitat composition or anthropogenic features over time and examining spatially-explicit covariates at multiple scales could improve prediction of lek density in Texas and other regions (Woodward et al. 2001, Fuhlendorf et al. 2002).

Management Implications

Based on our spatial analysis, wildlife managers should strive to maintain ≈50% of the landscape as shrubland patches for higher LPC lek densities in Texas. This can be achieved through habitat management techniques, such as prescribed burns or light grazing, which create a heterogeneous habitat of shrubs, grasses, and forbs (Applegate and Riley 1998, Bell et al. 2010). Our greatest predicted lek density estimates occurred in Gray, Hemphill, and Lipscomb counties in the northeast Panhandle and Bailey, Cochran, and Yoakum counties in the southwest Panhandle (Fig. 3.2; Appendix C). Given that most of our lek detections also occurred in these counties (Fig. 3.2; Appendix C), the construction or frequent use of roads for agriculture, oil or natural gas development, or other purposes, should be avoided in these areas to reduce negative impacts on LPCs. The construction of transmission lines for energy development should also be avoided in these areas. Regions in which predicted lek density is low (e.g., Carson county) may be better suited for energy development if it is imminent within the Texas occupied range or habitat improvement projects to satisfy LPC management objectives. Biologists, wildlife managers, and energy developers can also use our spatial models to predict how lek density may change in response to habitat management strategies or activities promoting the construction or use of roads within the Texas occupied range. This information will be necessary if LPCs are listed on the ESA. Another logical application of our spatial models would be to predict lek density outside the Texas occupied range to give wildlife managers an indication of other areas that could be targeted for LPC surveys or conservation efforts. However, our models should not be used to predict absolute density outside of our sampling frame.

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Literature Cited

American Wind Energy Association. 2012. U.S. Wind Industry: fourth quarter 2011 market report. American Wind Energy Association, Washington, D.C., USA.

Applegate, R. D., and T. Z. Riley. 1998. Lesser prairie-chicken management. Rangelands 20:13−15.

Arnold, T. W. 2010. Uninformative parameters and model selection using Akaike's Information Criterion. Journal of Wildlife Management 74:1175–1178.

Bell, L. A., S. D. Fuhlendorf, M. A. Patten, D. H. Wolfe, and S. K. Sherrod. 2010. Lesser prairie chicken hen and brood habitat use on sand shinnery oak. Rangeland Ecology and Management 63:478–486.

Bidwell, T. G. 2003. Ecology and management of the lesser prairie-chicken in Oklahoma. Oklahoma Cooperative Extension Service, E-970. Oklahoma State University, Stillwater, USA.

Buckland, S. T., D. R. Anderson, K. P. Burnham, J. L. Laake, D. L. Borchers, and L. Thomas. 2001. Introduction to distance sampling: estimating abundance of biological populations. Oxford University Press, New York, New York, USA.

Burnham, K. P., and D. R. Anderson. 2002. Model selection and multimodel inference: a practical information-theoretic approach. Second edition. Springer, New York, New York, USA.

Copelin, F. F. 1963. The lesser prairie chicken in Oklahoma. Technical Bulletin No. 6. Oklahoma Wildlife Conservation Department, Oklahoma City, USA:

Crawford, J. A., and E. G. Bolen. 1976*a*. Effects of land use on lesser prairie chickens in Texas. Journal of Wildlife Management 40:96−104.

Crawford, J. A., and E. G. Bolen. 1976*b*. Effects of lek disturbances on lesser prairie chickens. Southwestern Naturalist 21:238−240.

Davis, D. M., R. E. Horton, E. A. Odell, R. D. Rogers, and H. A. Whitlaw. 2008. Lesser prairie-chicken conservation initiative. Lesser prairie chicken interstate working group. Unpublished Report. Colorado Division of Wildlife, Fort Collins, USA.

Doherty, K. E., D. E. Naugle, B. L. Walker, and J. M. Graham. 2008. Greater sage-grouse winter habitat selection and energy development. Journal of Wildlife Management 72:187−195.

Electric Reliability Council of Texas. 2006. Analysis of transmission alternatives for Competitive Renewable Energy Zones in Texas. Electric Reliability Council of Texas, Austin, USA.

Elith, J., S. J. Phillips, T. Hastie, M. Dudik, Y. E. Chee, and C. J. Yates. 2011. A statistical explanation of MaxEnt for ecologists. Diversity and Distributions 17:43–57.

Fields, T. L., G. C. White, W. C. Gilgert, and R. D. Rodgers. 2006. Nest and brood survival of lesser prairie-chickens in west central Kansas. Journal of Wildlife Management 70:931–938.

Fiske, I. J.,and R. B. Chandler. 2011. Unmarked: an R package for fitting hierarchical models of wildlife occurrence and abundance. Journal of Statistical Software 43:1–23.

Fuhlendorf, S. D., A. J. Woodward, D. M. Leslie Jr., and J. S. Shackford. 2002. Multi-scale effects of habitat loss and fragmentation on lesser prairie-chicken populations of the US southern Great Plains. Landscape Ecology 17:617–628.

Gregory, A. J., L. B. McNew, T. J. Prebyl, B. K. Sandercock, and S. M. Wisely. 2011. Hierarchical modeling of lek habitats of greater prairie-chickens. Pages 21–32 *in* B. K. Sandercock, K. Martin, and G. Segelbacher, editors. Ecology, conservation, and management of grouse. Studies in Avian Biology, University of California Press, Berkeley, USA.

Hagen, C. A., B. E. Jamison, K. M. Giesen, and T. Z. Riley. 2004. Guidelines for managing lesser prairie-chicken populations and their habitats. Wildlife Society Bulletin 32:69−82.

Hagen, C. A. 2010. Impacts of energy development on prairie grouse ecology: a research synthesis. Transactions of the North American Wildlife and Natural Resources Conference 75:96−103.

Hagen, C. A., J. C. Pitman, T. M. Loughin, B. K. Sandercock, R. J. Robel, and R. D. Applegate. 2011. Impacts of anthropogenic features on habitat use by lesser prairie-chickens. Pages 63–75 *in* B. K. Sandercock, K. Martin, and G. Segelbacher, editors. Ecology, conservation, and management of grouse. Studies in Avian Biology, University of California Press, Berkeley, USA.

Hedley, S. L., and S. T. Buckland. 2004. Spatial models for line transect sampling. Journal of Agricultural, Biological, and Environmental Statistics 9:181−199.

Hiby, L., and M. B. Krishna. 2001. Line transect sampling from a curving path. Biometrics 57:727–731.

Holloran, M. J. 2005. Greater sage-grouse (*Centrocercusurophasianus*) population response to natural gas field development in western Wyoming. Dissertation, University of Wyoming, Laramie, USA.

Jackson, A.S., and R. DeArment. 1963. The lesser prairie chicken in the Texas Panhandle. Journal of Wildlife Management 27:733−737.

Jamison, B. E., J. A. Dechant, D. H. Johnson, L. D. Igl, C. M. Goldade, and B. R. Euliss. 2002. Effects of management practices on grassland birds: lesser prairie-chicken. Northern Prairie Wildlife Research Center, Jameston, North Dakota, USA.

Jarnevich, C. S., and M. K. Laubhan. 2011. Balancing energy development and conservation: a method utilizing species distribution models. Environmental Management 47: 926–936.

Kuvlesky, W. P., L. A. Brennan, M. L. Morrison, K. K. Boydston, B. M. Ballard, and F. C. Bryant. 2007. Wind energy development and conservation: challenges and opportunities. Journal of Wildlife Management 71:2487−2498.

Lyon, A. G., and S. H. Anderson. 2003. Potential gas development impacts on sage grouse nest initiation and movement. Wildlife Society Bulletin 31:486–491.

McNew, L. B., A. J. Gregory, S. M. Wisely, and B. K. Sandercock. 2011. Human-mediated selection on life-history traits of greater prairie-chickens. Pages 255–266 *in* B. K. Sandercock, K. Martin, and G. Segelbacher, editors. Ecology, conservation, and management of grouse. Studies in Avian Biology, University of California Press, Berkeley, USA.

McRoberts, J. T., M. J. Butler, W. B. Ballard, H. A. Whitlaw, D. A. Haukos, and M. C. Wallace. 2011. Detectability of lesser prairie-chicken leks: a comparison of surveys from aircraft. Journal of Wildlife Management 75:771−778.

Naugle, D. E., K. E. Doherty, B. L. Walker, M. J. Holloran, and H. E. Copeland. 2011. Energy development and greater sage-grouse. Pages 489–503 *in* S. T. Knicks and J.W. Connelly, editors. Greater sage-grouse: ecology and conservation of a landscape species and its habitats. Studies in Avian Biology, University of California-Press, Berkeley, USA.

Patten, M. A., D. H. Wolfe, E. Shochat, and S. K. Sherrod. 2005. Effects of microhabitat and microclimate selection on adult survivorship of the lesser prairie-chicken. Journal of Wildlife Management 69:1270–1278.

Pitman, J. C., C. A. Hagen, R. J. Robel, T. M. Loughin, and R. D. Applegate. 2005. Location and success of lesser prairie-chicken nests in relation to vegetation and human disturbance. Journal of Wildlife Management 69:1259–1269.

Platts. 2011. Electric transmission lines. Platts, Westminster, Colorado, USA.

PRISM Climate Group, Oregon State University. 2011. PRISM homepage. <http://www.prism.oregonstate.edu>. Accessed 4 September 2011.

Pruett, C. L., M. A. Patten, and D. H. Wolfe. 2009. Avoidance behavior by prairie grouse: implications for development of wind energy. Conservation Biology 23:1253−1259.

Railroad Commission of Texas. 2011. Oil and Gas Well Records. <http://www.rrc.state.tx.us/data/wells/wellrecords.php>. Accessed 1 October 2011.

R Development Core Team. 2011. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. <http://www.R-project.org>. Accessed 22 August 2011.

Ribic, C.A., and D.W. Sample. 2001. Associations of grassland birds with landscape factors in southern Wisconsin. American Midland Naturalist 146:105–121.

Royle, J. A., D. K. Dawson, and S. Bates. 2004. Modeling abundance effects in distance sampling. Ecology 85:1591–1597.

Royle, J. A., R. B. Chandler, C. Yackulic, and J. D. Nichols. 2012. Likelihood analysis of species occurrence probability from presence-only data for modelling species distributions. Methods in Ecology and Evolution. doi: 10.1111/j.2041-210X.2011.00182.x

Sullivan, R. M., J. P. Hughes, and J. E. Lionberger. 2000. Review of the historical and present status of the lesser prairie-chicken (*Tympanuchus pallidicinctus*) in Texas. The Prairie Naturalist 32:177−188.

Taylor, M. A., and F. S. Guthery. 1980. Status, ecology, and management of the lesser prairie chicken. General Technical Report RM−77, U.S. Department of Agriculture, Forest Service, Rocky Mountain Forest and Range Experimental Station, Fort Collins, USA.

Texas Department of Transportation. 2011. TxDOT_Roadways. Transportation Planning and Program Division, Data Analysis Branch, Austin, USA.

Thompson, W. L., G. C. White, and C. Gowan. 1998. Monitoring vertebrate populations. Academic Press, San Diego, California, USA.

Timmer, J. M. 2012. Abundance and density of lesser prairie-chicken leks in the Texas, Chapter II Thesis, Texas Tech University, Lubbock, USA.

U.S. Department of Agriculture. 2008. USDA, National Agricultural Statistics Service, 2008 Texas cropland data layer. 2008 edition. U.S. Department of Agriculture, National Agricultural Statistics Service Marketing and Information Services Office, Washington, D.C.

U.S. Environmental Protection Agency. 1998. DOT/FHA major roads for CONUS, Alaska, and Hawaii in BASINS. Office of Water, Washington, D.C., USA.

U.S. Fish and Wildlife Service. 2008. Candidate status review. Federal Register 73:75179−75180.

U.S. Fish and Wildlife Service. 1998. Endangered and threatened wildlife and plants; 12-month finding for a petition to list the lesser prairie-chicken as threatened and designate critical habitat. Federal Register 63:31400–31406.

Walker, B. L., D. E. Naugle, and K. E. Doherty. 2007. Greater sage-grouse population response to energy development and habitat loss. Journal of Wildlife Management 71:2644−2654.

Woodward, A. J., S. D. Fuhlendorf, D. M. Leslie Jr., and J. Shackford. 2001. Influence of landscape composition and change on lesser prairie-chicken (*Tympanuchus pallidicinctus*) populations. The American Midland Naturalist 145:261–274.

Table 3.1. Landscape covariates included in spatial models for predicting lesser prairie-chicken lek density in Texas and a description of each covariate.

Covariate[a]	Description
GRASS	Percent of the quadrat composed of grassland patches (native grassland, CRP, or idle cropland comprising >80% of the total vegetation) including a quadratic term.
SHRUB	Percent of the quadrat composed of shrubland patches (shrubs <5 m tall comprising ≥20% of the total vegetation) including a quadratic term.
AGP	Average patch size (km^2) of grassland patches that overlapped the quadrat.
ASP	Average patch size (km^2) of shrubland patches that overlapped the quadrat.
GRAIN	Percent of the quadrat composed of grain field patches (e.g., winter wheat, corn, or grain sorghum).
EDGE	Edge density for all landcover patches (km/km^2).
HWY	Paved road density (km/km^2).
DIRT	Unpaved road density (km/km^2).
ROADS	Paved and unpaved road density (km/km^2).
TRANSM	Transmission line (>69 kv) density (km/km^2).

Table 3.1. Continued

Covariate[a]	Description
WELL	Active oil and gas well density (wells/km^2).

[a] Each covariate estimated for a 12.96-km^2 quadrat.

Table 3.2. Three model sets of hierarchical distance sampling models predicting lesser prairie-chicken lek density in Texas. For each candidate model, we give –2×log-likelihood (–2LL), number of parameters (*K*), Akaike's Information Criterion (AIC), difference in AIC compared to lowest AIC of the model set (Δ_i), AIC weight (w_i), predicted lek abundance (N), and coefficient of variation for abundance (*cv*).

Model[a]	–2LL	*K*	AIC	Δ_i	w_i	N[b]	*cv*
Vegetation Model Set							
SHRUB	937.098	4	945.098	0.000	0.487	246.3	0.136
SHRUB + GRAIN	936.558	5	946.558	1.460	0.235	245.1	0.176
SHRUB + GRAIN + EDGE	936.026	6	948.026	2.927	0.113	245.3	0.137
GRASS	941.501	4	949.501	4.403	0.054	243.3	0.130
GRASS + EDGE	940.673	5	950.673	5.575	0.030	243.5	0.145
GRAIN + EDGE	944.137	4	952.137	7.039	0.014	148.5	0.104
AGP	946.475	3	952.475	7.377	0.012	248.9	0.132
AGP + EDGE	944.570	4	952.570	7.471	0.012	249.9	0.137

Table 3.2. Continued

Model[a]	–2LL	K	AIC	Δ_i	w_i	N[b]	cv
ASP + EDGE	945.029	4	953.029	7.931	0.009	251.0	0.134
AGP + GRAIN + EDGE	943.516	5	953.516	8.417	0.007	250.3	0.137
AGP + GRAIN	945.642	4	953.642	8.544	0.007	249.2	0.136
GRAIN	947.967	3	953.967	8.869	0.006	250.1	0.134
ASP	948.042	3	954.042	8.943	0.006	250.7	0.137
ASP + GRAIN + EDGE	944.108	5	954.108	9.009	0.005	251.2	0.132
ASP + GRAIN	947.489	4	955.489	10.391	0.003	251.1	0.134
SHRUB + EDGE	961.846	5	971.846	26.747	<0.001	145.9	0.118
GRASS + GRAIN	964.081	5	974.081	28.983	<0.001	244.4	0.136
GRASS + GRAIN + EDGE	963.872	6	975.872	30.774	<0.001	144.6	0.102
EDGE	969.874	3	975.874	30.775	<0.001	148.2	0.099

Table 3.2. Continued

Model[a]	–2LL	K	AIC	Δ_i	w_i	N[b]	cv
Road Model Set							
HWY + DIRT	937.134	4	945.134	0.000	0.716	249.5	0.135
DIRT	940.988	3	946.988	1.854	0.284	251.9	0.139
ROADS	961.990	3	967.990	22.855	<0.001	249.8	0.134
HWY	968.957	3	974.957	29.823	<0.001	246.6	0.137
Energy Model Set							
TRANSM	944.773	3	950.773	0.000	0.636	248.3	0.132
TRANSM + WELL	944.558	4	952.558	1.785	0.260	247.9	0.133
WELL	948.394	3	954.394	3.621	0.104	249.6	0.140

[a] Covariates described in Table 3.1.

[b] Predicted lek abundance for each model.

Table 3.3. Best overall hierarchical distance sampling models predicting lesser prairie-chicken lek density in Texas. For each candidate model, we give –2×log-likelihood (–2LL), number of parameters (*K*), Akaike's Information Criterion (AIC), difference in AIC compared to lowest AIC of the model set (Δ_i), AIC weight (w_i), predicted lek abundance (N), and coefficient of variation for abundance (*cv*).

Model[a]	–2LL	*K*	AIC	Δ_i	w_i	N[b]	*cv*
SHRUB + HWY + DIRT	926.926	6	938.926	0.000	0.826	248.5	0.136
TRANSM + HWY + DIRT	934.467	5	944.467	5.540	0.052	249.0	0.135
SHRUB	937.098	4	945.098	6.172	0.038	246.3	0.136
HWY + DIRT	937.150	4	945.150	6.224	0.037	249.5	0.135
DIRT + TRANSM	937.584	4	945.584	6.657	0.030	250.9	0.144
DIRT	940.988	3	946.988	8.062	0.015	251.9	0.139
TRANSM	944.773	3	950.773	11.846	0.002	248.3	0.132
NULL	948.407	2	952.407	13.480	0.001	249.7	0.136
SHRUB + HWY +DIRT+TRANSM	949.199	7	963.199	24.273	<0.001	146.5	0.101

Table 3.3. Continued

Model[a]	–2LL	K	AIC	Δ_i	w_i	N[b]	*cv*
SHRUB + DIRT +TRANSM	952.503	6	964.503	25.577	<0.001	248.9	0.144
SHRUB + DIRT	956.009	5	966.009	27.082	<0.001	148.1	0.102
SHRUB + TRANSM	956.967	5	966.967	28.040	<0.001	244.8	0.133

[a] Covariates described in Table 3.1.

[b] Predicted lek abundance for each model.

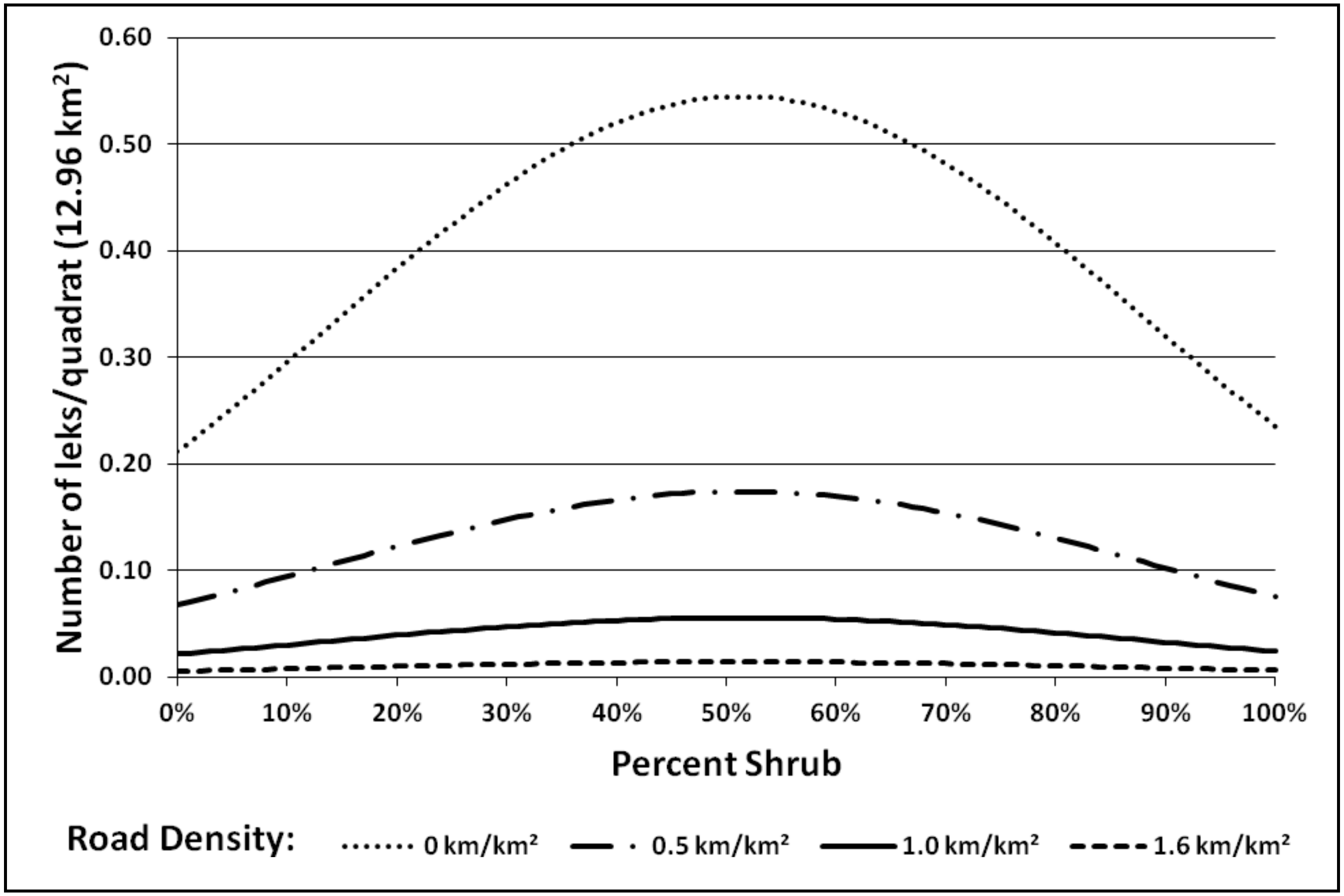

Figure 3.1. Predicted lesser prairie-chicken lek density in response to the percent of the landscape composed of shrubland patches and road density (km/km^2) in the Texas occupied range.

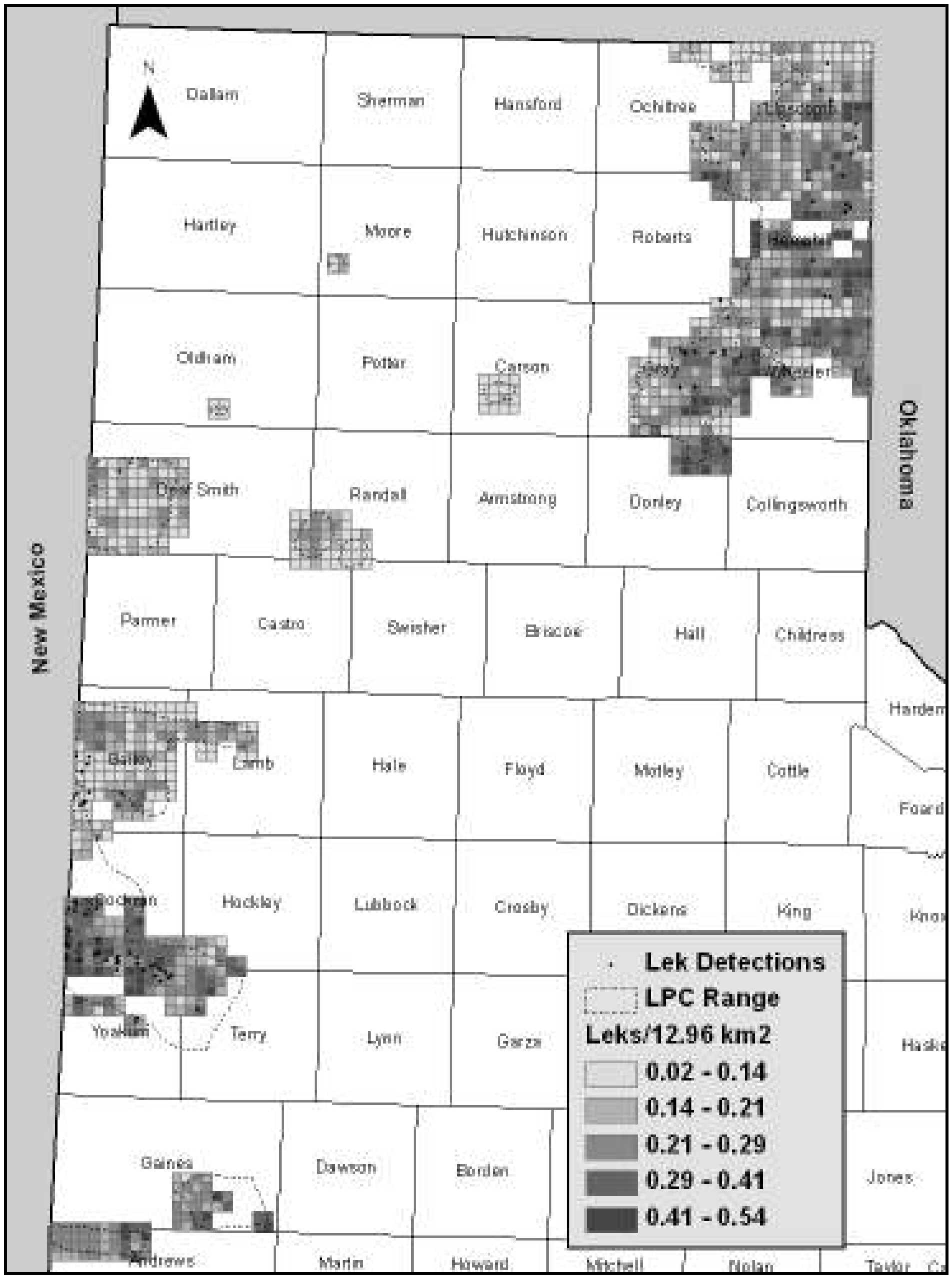

Figure 3.2. Predicted lesser prairie-chicken (LPC) lek density for 12.96 km^2 quadrats covering the Texas occupied LPC based on a hierarchical distance sampling model. Whites areas inside the occupied range were classified as non-LPC habitat and were not included in the sampling frame.

APPENDIX A

CORRELATIONS AMONG LANDSCAPE COVARIATES

Table A.1. Table of Pearson's correlation coefficients (r) and p-values (P) for landscape covariates used in spatially-explicit models predicting lesser prairie-chicken lek density in the Texas occupied range.

Covariates[a]		GRASS	SHRUB	GRAIN	AGP	ASP	EDGE	TRANSM	HWY	DIRT	WELL	ROADS
							P:					
GRASS			<0.001	0.002	<0.001	<0.001	<0.001	>0.999	0.333	>0.999	<0.001	>0.999
SHRUB		–0.828		<0.001	<0.001	<0.001	0.226	>0.999	>0.999	<0.001	<0.001	<0.001
GRAIN		–0.136	–0.368		<0.001	0.006	0.001	>0.999	0.036	<0.001	<0.001	<0.001
AGP		0.382	–0.265	–0.165		0.612	<0.001	>0.999	0.015	0.001	0.047	<0.001
ASP		–0.398	0.500	–0.127	–0.070		<0.001	0.897	0.065	<0.001	>0.999	<0.001
EDGE	*r:*	–0.251	0.086	0.148	–0.399	–0.298		>0.999	<0.001	<0.001	0.047	<0.001
TRANSM		–0.044	0.036	–0.002	0.019	–0.063	–0.014		0.141	>0.999	0.033	0.156
HWY		–0.080	–0.029	0.109	–0.119	–0.102	0.205	0.092		>0.999	<0.001	<0.001
DIRT		0.059	–0.279	0.326	–0.144	–0.204	0.241	0.051	0.021		0.445	<0.001
WELL		–0.310	0.385	–0.213	–0.106	0.037	0.106	0.111	0.191	0.075		>0.999
ROADS		0.005	–0.246	0.330	–0.184	–0.224	0.311	0.093	0.563	0.838	0.042	

[a] Covariates described in Table 3.1.

APPENDIX B

R SCRIPT FOR HIERARCHICAL DISTANCE SAMPLING

```
# Load the needed R-packages. #
library(unmarked)
library(Rcmdr)

# Load the data. #
DIST = read.table("C:
        /distdata.csv",header=TRUE,colClasses=c("factor","numeric","numeric","numeri
        c"),sep=",")
LENGTHS = read.table("C:/ length.csv",header=FALSE,colClasses="numeric",sep=",")
COVS = read.table("C:/
        covs.csv",header=TRUE,colClasses=c(rep("numeric",11),"factor","factor"),sep=",
        ")

# Check correlations. #
covs.corr =
        rcorr.adjust(COVS[,c("GRASS","SHRUB","GRAIN","AGP"
        "ASP","EDGE","TRANSM","HWY","DIRT","ROADS","WELL")],
        type="pearson")

# Show summary of correlations. #
covs.corr

# Export correlation statistics to table. #
write.table(covs.corr$R$r,file="C:/
        corr_r.csv",append=FALSE,sep=",",row.names=FALSE,col.names=TRUE)
write.table(covs.corr$P,file="C:/
        corr_p.csv",append=FALSE,sep=",",row.names=FALSE,col.names=TRUE)

# Do these things to standardize your covariates. #
mean.transm = mean(COVS$TRANSM)
std.transm = sd(COVS$TRANSM)
COVS$RETRANSM = (COVS$TRANSM-mean.transm)/std.transm

mean.grass = mean(COVS$GRASS)
std.grass = sd(COVS$GRASS)
COVS$REGRASS = (COVS$GRASS-mean.grass)/std.grass
COVS$REGRASS2 = COVS$REGRASS*COVS$REGRASS

mean.shrub = mean(COVS$SHRUB)
std.shrub = sd(COVS$SHRUB)
COVS$RESHRUB = (COVS$SHRUB-mean.shrub)/std.shrub
COVS$RESHRUB2 = COVS$RESHRUB*COVS$RESHRUB
```

```
mean.dirt = mean(COVS$DIRT)
std.dirt = sd(COVS$DIRT)
COVS$REDIRT = (COVS$DIRT-mean.dirt)/std.dirt

# Show summary of covariate data. #
summary(COVS)

# Put the data into "multinomial format" using DistData function. #
yDat = formatDistData(DIST, distCol="distance", transectNameCol="transect",
        dist.breaks=c(0, 35, 50, 70, 90, 120, 150, 179))

# Make the unmarkedFrameDS. #
umf = unmarkedFrameDS(y=as.matrix(yDat), siteCovs=COVS, survey="line",
        dist.breaks=c(0, 35, 50, 70, 90, 120, 150, 179), tlength=LENGTHS$V1,
        unitsIn="m")

# Show summary of the unmarkedFrame. #
summary(umf)

# Plot histogram of the detection distances. #
hist(umf, xlab="distance (m)", main="", cex.lab=0.8, cex.axis=0.8)

# Fit the base detection functions and pick one to use. #
hn = distsamp(~1 ~1, umf, keyfun="halfnorm", output="density")
haz = distsamp(~1 ~1, umf, keyfun="hazard", output="density")
unif = distsamp(~1 ~1, umf, keyfun="uniform", output="density")
CDS_fitlist = fitList(hn,haz,unif)      # Create the fit list.#
ms1 = modSel(CDS_fitlist)     # Rank the models by AIC.#

# Create a data frame of the model set's statistics. #
MS1.modelstats = as(ms1, "data.frame")

# Look at the hazard-rate CDS model (poorly performing model). #
haz
backTransform(haz, type="state")
hist(haz, xlab="distance (m)", main="", cex.lab=0.8, cex.axis=0.8)

# Look at the half-normal CDS model. #
hn
backTransform(hn, type="state")
backTransform(hn, type="det")
hist(hn, xlab="distance (m)", main="", cex.lab=0.8, cex.axis=0.8)
```

```
# Fit the roads model set. #
hn_hwy = distsamp(~1 ~HWY, umf, keyfun="halfnorm", output="density")
hn_dirt = distsamp(~1 ~REDIRT, umf, keyfun="halfnorm", output="density")
hn_hwy_dirt = distsamp(~1 ~HWY+REDIRT, umf, keyfun="halfnorm",
        output="density")
hn_roads = distsamp(~1 ~ROADS, umf, keyfun="halfnorm", output="density")
roads_fitlist = fitList(hn_hwy,hn_dirt,hn_roads)
ms2 = modSel(roads_fitlist)

# Look at break-down of top roads models; hwy and dirt are both significant. #
hn_hwy_dirt
hn_dirt

# Create a data frame of the model set's statistics. #
MS2.modelstats = as(ms2, "data.frame")

# Export table with AIC values for roads model set. #
write.table(cbind(MS2.modelstats$formula,MS2.modelstats$negLogLike,MS2.modelstat
        s$nPars,MS2.modelstats$AIC,MS2.modelstats$delta,MS2.modelstats$AICwt),fil
        e="C:/roads_models.csv",append=FALSE,sep=",",row.names=FALSE,col.names
        =TRUE)

# Fit the energy model set. #
hn_transm = distsamp(~1 ~RETRANSM, umf, keyfun="halfnorm", output="density")
hn_well = distsamp(~1 ~WELL, umf, keyfun="halfnorm", output="density")
hn_transm_well = distsamp(~1 ~RETRANSM+WELL, umf, keyfun="halfnorm",
        output="density")
energy_fitlist = fitList(hn_transm,hn_well,hn_transm_well)
ms3 = modSel(energy_fitlist)

# Look at break-down of top energy models; oil and gas not significant. #
hn_transm
hn_transm_well

# Create a data frame of the model set's statistics. #
MS3.modelstats = as(ms3, "data.frame")

# Export table with AIC values for energy model set. #
write.table(cbind(MS3.modelstats$formula,MS3.modelstats$negLogLike,MS3.modelstat
        s$nPars,MS3.modelstats$AIC,MS3.modelstats$delta,MS3.modelstats$AICwt),fil
        e="C:/
        energy_models.csv",append=FALSE,sep=",",row.names=FALSE,col.names=TR
        UE)
```

```
# Fit the vegetation model set. #
hn_grass = distsamp(~1 ~REGRASS+REGRASS2, umf, keyfun="halfnorm",
        output="density")
hn_asp = distsamp(~1 ~ASP, umf, keyfun="halfnorm", output="density")
hn_agp = distsamp(~1 ~AGP, umf, keyfun="halfnorm", output="density")
hn_shrub = distsamp(~1 ~RESHRUB+RESHRUB2, umf, keyfun="halfnorm",
        output="density")
hn_grain = distsamp(~1 ~GRAIN, umf, keyfun="halfnorm", output="density")
hn_edge = distsamp(~1 ~EDGE, umf, keyfun="halfnorm", output="density")
hn_grass_grain = distsamp(~1 ~REGRASS+REGRASS2+GRAIN, umf,
        keyfun="halfnorm", output="density")
hn_asp_grain = distsamp(~1 ~ASP+GRAIN, umf, keyfun="halfnorm", output="density")
hn_agp_grain = distsamp(~1 ~AGP+GRAIN, umf, keyfun="halfnorm",
        output="density")
hn_shrub_grain = distsamp(~1 ~RESHRUB+RESHRUB2+GRAIN, umf,
        keyfun="halfnorm", output="density")
hn_grass_edge = distsamp(~1 ~REGRASS+REGRASS2+EDGE, umf,
        keyfun="halfnorm", output="density")
hn_asp_edge = distsamp(~1 ~ASP+EDGE, umf, keyfun="halfnorm", output="density")
hn_agp_edge = distsamp(~1 ~AGP+EDGE, umf, keyfun="halfnorm", output="density")
hn_grain_edge = distsamp(~1 ~GRAIN+EDGE, umf, keyfun="halfnorm",
        output="density")
hn_shrub_edge = distsamp(~1 ~RESHRUB+RESHRUB2+EDGE, umf,
        keyfun="halfnorm", output="density")
hn_grass_grain_edge = distsamp(~1 ~REGRASS+REGRASS2+GRAIN+EDGE, umf,
        keyfun="halfnorm", output="density")
hn_asp_grain_edge = distsamp(~1 ~ASP+GRAIN+EDGE, umf, keyfun="halfnorm",
        output="density")
hn_agp_grain_edge = distsamp(~1 ~AGP+GRAIN+EDGE, umf, keyfun="halfnorm",
        output="density")
hn_shrub_grain_edge = distsamp(~1 ~RESHRUB+RESHRUB2+GRAIN+EDGE, umf,
        keyfun="halfnorm", output="density")
veg_fitlist =
        fitList(hn_grass,hn_asp,hn_agp,hn_shrub,hn_grain,hn_edge,hn_asp_grain,hn_agp
        _grain,hn_grass_grain,hn_shrub_grain,hn_grass_edge,hn_asp_edge,hn_agp_edge,
        hn_shrub_edge,hn_grain_edge,hn_grass_grain_edge,hn_asp_grain_edge,hn_agp_
        grain_edge,hn_shrub_grain_edge)
ms4 = modSel(veg_fitlist)

# Look at break-down of top veg models; grain not significant. #
hn_shrub
hn_shrub_grain
```

```
# Create a data frame of the model set's statistics. #
MS4.modelstats = as(ms4, "data.frame")

# Export table with AIC values for veg model set. #
write.table(cbind(MS4.modelstats$formula,MS4.modelstats$negLogLike,MS4.modelstat
        s$nPars,MS4.modelstats$AIC,MS4.modelstats$delta,MS4.modelstats$AICwt),fil
        e="C:/veg_models.csv",append=FALSE,sep=",",row.names=FALSE,col.names=
        TRUE)

# Best models from the vegetation, road, and energy model sets. #
pre_best_fitlist = fitList(hn,hn_dirt,hn_hwy_dirt,hn_transm,hn_shrub)
ms5 = modSel(pre_best_fitlist)

# Create a data frame of the best models from each set. #
MS5.modelstats = as(ms5, "data.frame")

# Export table with AIC values for best of each model set. #
write.table(cbind(MS5.modelstats$formula,MS5.modelstats$negLogLike,MS5.modelstat
        s$nPars,MS5.modelstats$AIC,MS5.modelstats$delta,MS5.modelstats$AICwt),fil
        e="C:/
        best_each_models.csv",append=FALSE,sep=",",row.names=FALSE,col.names=T
        RUE)

# Fit the final model set. #
hn = distsamp(~1 ~1, umf, keyfun="halfnorm", output="density")
hn_shrub = distsamp(~1 ~RESHRUB+RESHRUB2, umf, keyfun="halfnorm",
        output="density")
hn_dirt = distsamp(~1 ~REDIRT, umf, keyfun="halfnorm", output="density")
hn_hwy_dirt = distsamp(~1 ~HWY+REDIRT, umf,
        keyfun="halfnorm",output="density", starts=c(-8.577,-1.228,-0.316,4.48))
hn_transm = distsamp(~1 ~TRANSM, umf, keyfun="halfnorm", output="density")
hn_shrub_dirt = distsamp(~1 ~RESHRUB+RESHRUB2+REDIRT, umf,
        keyfun="halfnorm", output="density", method="Nelder-Mead")
hn_shrub_dirt #look at model breakdown to get starting values.#
hn_shrub_dirt = distsamp(~1 ~RESHRUB+RESHRUB2+REDIRT, umf,
        keyfun="halfnorm", output="density",starts=c(-9.014,0.529,-0.286,-0.286,9.79))
hn_shrub_transm = distsamp(~1 ~RESHRUB+RESHRUB2+RETRANSM, umf,
        keyfun="halfnorm", output="density")
hn_dirt_transm = distsamp(~1 ~REDIRT+RETRANSM, umf, keyfun="halfnorm",
        output="density")
hn_shrub_hwy_dirt = distsamp(~1 ~RESHRUB+RESHRUB2+HWY+REDIRT, umf,
        keyfun="halfnorm", output="density")
```

```
hn_shrub_hwy_dirt_transm = distsamp(~1
        ~RESHRUB+RESHRUB2+HWY+REDIRT+RETRANSM, umf,
        keyfun="halfnorm", output="density",method="Nelder-Mead")
hn_shrub_hwy_dirt_transm #look at model breakdown to get starting values.#
hn_shrub_hwy_dirt_transm = distsamp(~1
        ~RESHRUB+RESHRUB2+HWY+REDIRT+RETRANSM, umf,
        keyfun="halfnorm", output="density",starts=c(-8.905,0.556,-0.292,-1.045,-
        0.281,-0.196,9.59))
hn_shrub_dirt_transm = distsamp(~1
        ~RESHRUB+RESHRUB2+REDIRT+RETRANSM, umf, keyfun="halfnorm",
        output="density")
hn_transm_hwy_dirt = distsamp(~1 ~RETRANSM+HWY+REDIRT, umf,
        keyfun="halfnorm", output="density")
fitsbest =
        fitList(hn,hn_shrub,hn_dirt,hn_transm,hn_hwy_dirt,hn_shrub_transm,hn_dirt_tra
        nsm,hn_shrub_hwy_dirt,hn_shrub_hwy_dirt_transm,hn_shrub_dirt_transm,hn_tra
        nsm_hwy_dirt,hn_shrub_dirt)
ms6 = modSel(fitsbest)

# Examine all the coefficents and SEs for the final model set. #
coef(ms6)
SE(ms6)

# Create a data frame of the final model set's statistics. #
MS6.modelstats = as(ms6, "data.frame")

# Export table with AIC values for top models. #
write.table(cbind(MS6.modelstats$formula,MS6.modelstats$negLogLike,MS6.modelstat
        s$nPars,MS6.modelstats$AIC,MS6.modelstats$delta,MS6.modelstats$AICwt),fil
        e="C:/
        top_models.csv",append=FALSE,sep=",",row.names=FALSE,col.names=TRUE)

# Change units in best model to KM^2. #
hn_shrub_hwy_dirt_km2 = distsamp(~1 ~RESHRUB+RESHRUB2+HWY+REDIRT,
        umf, keyfun="halfnorm", output="density", unitsOut="kmsq")

# The best model. #
hn_shrub_hwy_dirt_km2
backTransform(hn_shrub_hwy_dirt_km2, type="det")
exp(coef(hn_shrub_hwy_dirt_km2, type="state",altNames=TRUE))

# Make a list of the best model from the final model set. #
topfits = fitList(hn_shrub_hwy_dirt_km2)
```

```
ms7 = modSel(topfits)

# Create a data frame of the model set's statistics. #
MS7.modelstats = as(ms7, "data.frame")

# GOF Analysis function. #
freeTuke = function(fm) {
  observed = getY(fm@data)
  expected = fitted(fm)
  sum((sqrt(observed)-sqrt(expected))^2)
}

# Parametric bootstrap GOF Test for the top model, it takes awhile. #
GOF_hn_shrub_hwy_dirt_km2 = parboot(hn_shrub_hwy_dirt_km2, freeTuke,
        nsim=1000, report=2)
plot(GOF_hn_shrub_hwy_dirt_km2)

# Show the GOF statistics. #
GOF_hn_shrub_hwy_dirt_km2

# Get AIC weights of top model. #
best.AICwt = MS7.modelstats$AICwt

# Change units in all models to KM^2. #
hn_shrub_grain_km2 = distsamp(~1 ~RESHRUB+RESHRUB2+GRAIN, umf,
        keyfun="halfnorm", output="density", unitsOut="kmsq")
hn_shrub_edge_km2 = distsamp(~1 ~RESHRUB+RESHRUB2+EDGE, umf,
        keyfun="halfnorm", output="density", unitsOut="kmsq")
hn_shrub_grain_edge_km2 = distsamp(~1 ~RESHRUB+RESHRUB2+GRAIN+EDGE,
        umf, keyfun="halfnorm", output="density", unitsOut="kmsq")
hn_grass_grain_edge_km2 = distsamp(~1 ~REGRASS+REGRASS2+GRAIN+EDGE,
        umf, keyfun="halfnorm", output="density", unitsOut="kmsq")
hn_grain_edge_km2 = distsamp(~1 ~GRAIN+EDGE, umf, keyfun="halfnorm",
        output="density", unitsOut="kmsq")
hn_agp_km2 = distsamp(~1 ~AGP, umf, keyfun="halfnorm", output="density",
        unitsOut="kmsq")
hn_agp_edge_km2 = distsamp(~1 ~AGP+EDGE, umf, keyfun="halfnorm",
        output="density", unitsOut="kmsq")
hn_asp_km2 = distsamp(~1 ~ASP, umf, keyfun="halfnorm", output="density",
        unitsOut="kmsq")
hn_asp_edge_km2 = distsamp(~1 ~ASP+EDGE, umf, keyfun="halfnorm",
        output="density", unitsOut="kmsq")
```

```
hn_agp_grain_edge_km2 = distsamp(~1 ~AGP+GRAIN+EDGE, umf,
        keyfun="halfnorm", output="density", unitsOut="kmsq")
hn_agp_grain_km2 = distsamp(~1 ~AGP+GRAIN, umf, keyfun="halfnorm",
        output="density", unitsOut="kmsq")
hn_grain_km2 = distsamp(~1 ~GRAIN, umf, keyfun="halfnorm", output="density",
        unitsOut="kmsq")
hn_asp_grain_edge_km2 = distsamp(~1 ~ASP+GRAIN+EDGE, umf,
        keyfun="halfnorm", output="density", unitsOut="kmsq")
hn_asp_grain_km2 = distsamp(~1 ~ASP+GRAIN, umf, keyfun="halfnorm",
        output="density", unitsOut="kmsq")
hn_grass_grain_km2 = distsamp(~1 ~REGRASS+REGRASS2+GRAIN, umf,
        keyfun="halfnorm", output="density", unitsOut="kmsq")
hn_grass_edge_km2 = distsamp(~1 ~REGRASS+REGRASS2+EDGE, umf,
        keyfun="halfnorm", output="density", unitsOut="kmsq")
hn_well_km2 = distsamp(~1 ~WELL, umf, keyfun="halfnorm", output="density",
        unitsOut="kmsq")
hn_transm_km2 = distsamp(~1 ~RETRANSM, umf, keyfun="halfnorm",
        output="density", unitsOut="kmsq")
hn_transm_well_km2 = distsamp(~1 ~RETRANSM+WELL, umf, keyfun="halfnorm",
        output="density", unitsOut="kmsq")
hn_hwy_km2 = distsamp(~1 ~HWY, umf, keyfun="halfnorm", output="density",
        unitsOut="kmsq")
hn_edge_km2 = distsamp(~1 ~EDGE, umf, keyfun="halfnorm", output="density",
        unitsOut="kmsq")
hn_dirt_km2 = distsamp(~1 ~REDIRT, umf, keyfun="halfnorm", output="density",
        unitsOut="kmsq")
hn_roads_km2 = distsamp(~1 ~ROADS, umf, keyfun="halfnorm", output="density",
        unitsOut="kmsq")
hn_km2 = distsamp(~1 ~1, umf, keyfun="halfnorm", output="density",
        unitsOut="kmsq")
hn_dirt_transm_km2 = distsamp(~1 ~REDIRT+RETRANSM, umf, keyfun="halfnorm",
        output="density", unitsOut="kmsq")
hn_hwy_dirt_km2= distsamp(~1 ~HWY+REDIRT, umf,
        keyfun="halfnorm",output="density", starts=c(-8.577,-1.228,-
        0.316,4.48),unitsOut="kmsq")
hn_grass_km2= distsamp(~1 ~REGRASS+REGRASS2, umf, keyfun="halfnorm",
        output="density",unitsOut="kmsq")
hn_shrub_dirt_km2= distsamp(~1 ~RESHRUB+RESHRUB2+REDIRT, umf,
        keyfun="halfnorm", output="density",starts=c(-9.014,0.529,-0.286,-
        0.286,9.79),unitsOut="kmsq")
hn_shrub_dirt_transm_km2= distsamp(~1
        ~RESHRUB+RESHRUB2+REDIRT+RETRANSM, umf, keyfun="halfnorm",
        output="density",unitsOut="kmsq")
```

```
hn_shrub_hwy_dirt_transm_km2= distsamp(~1
        ~RESHRUB+RESHRUB2+HWY+REDIRT+RETRANSM, umf,
        keyfun="halfnorm", output="density",starts=c(-8.905,0.556,-0.292,-1.045,-
        0.281,-0.196,9.59),unitsOut="kmsq")
hn_transm_hwy_dirt_km2= distsamp(~1 ~RETRANSM+HWY+REDIRT, umf,
        keyfun="halfnorm", output="density",unitsOut="kmsq")
hn_shrub_transm_km2= distsamp(~1 ~RESHRUB+RESHRUB2+RETRANSM, umf,
        keyfun="halfnorm", output="density",unitsOut="kmsq")
hn_shrub_km2= distsamp(~1 ~RESHRUB+RESHRUB2, umf, keyfun="halfnorm",
        output="density",unitsOut="kmsq")

# Load grid of covariates for prediction of population size. #
GRID = read.table("C:/ predict2.csv",header=TRUE,sep=",")

# Do these things to standardize your covariates in the prediction grid, but use the mean
        and std from original data. #
GRID$RETRANSM = (GRID$TRANSM-mean.transm)/std.transm
GRID$REDIRT = (GRID$DIRT-mean.dirt)/std.dirt
GRID$REGRASS = (GRID$GRASS-mean.grass)/std.grass
GRID$REGRASS2 = GRID$REGRASS*GRID$REGRASS
GRID$RESHRUB = (GRID$SHRUB-mean.shrub)/std.shrub
GRID$RESHRUB2 = GRID$RESHRUB*GRID$RESHRUB

# Get predicted values for all models. #
pred1 = predict(hn_shrub_transm_km2, type="state", newdata=GRID)
pred2 = predict(hn_shrub_km2, type="state", newdata=GRID)
pred3 = predict(hn_grain_km2, type="state", newdata=GRID)
pred4 = predict(hn_agp_km2, type="state", newdata=GRID)
pred5 = predict(hn_asp_km2, type="state", newdata=GRID)
pred6 = predict(hn_edge_km2, type="state", newdata=GRID)
pred7 = predict(hn_shrub_grain_km2, type="state", newdata=GRID)
pred8 = predict(hn_shrub_edge_km2, type="state", newdata=GRID)
pred9 = predict(hn_shrub_grain_edge_km2, type="state", newdata=GRID)
pred10 = predict(hn_grain_edge_km2, type="state", newdata=GRID)
pred11 = predict(hn_agp_edge_km2, type="state", newdata=GRID)
pred12 = predict(hn_asp_edge_km2, type="state", newdata=GRID)
pred13 = predict(hn_agp_grain_km2, type="state", newdata=GRID)
pred14 = predict(hn_agp_grain_edge_km2, type="state", newdata=GRID)
pred15 = predict(hn_asp_grain_edge_km2, type="state", newdata=GRID)
pred16 = predict(hn_asp_grain_km2, type="state", newdata=GRID)
pred17 = predict(hn_dirt_km2, type="state", newdata=GRID)
pred18 = predict(hn_hwy_km2, type="state", newdata=GRID)
pred19 = predict(hn_roads_km2, type="state", newdata=GRID)
```

```
pred20 = predict(hn_transm_km2, type="state", newdata=GRID)
pred21 = predict(hn_well_km2, type="state", newdata=GRID)
pred22 = predict(hn_transm_well_km2, type="state", newdata=GRID)
pred23 = predict(hn_dirt_transm_km2, type="state", newdata=GRID)
pred24 = predict(hn_grass_grain_km2, type="state", newdata=GRID)
pred25 = predict(hn_grass_grain_edge_km2, type="state", newdata=GRID)
pred26 = predict(hn_grass_edge_km2, type="state", newdata=GRID)
pred27 = predict(hn_km2, type="state", newdata=GRID)
pred28 = predict(hn_hwy_dirt_km2, type="state", newdata=GRID)
pred29 = predict(hn_grass_km2, type="state", newdata=GRID)
pred30 = predict(hn_shrub_dirt_km2, type="state", newdata=GRID)
pred31 = predict(hn_shrub_dirt_transm_km2, type="state", newdata=GRID)
pred32 = predict(hn_shrub_hwy_dirt_km2, type="state", newdata=GRID)
pred33 = predict(hn_shrub_hwy_dirt_transm_km2, type="state", newdata=GRID)
pred34 = predict(hn_transm_hwy_dirt_km2, type="state", newdata=GRID)

# Convert predicted density to N per quadrat. #
predD1 = as.vector(pred1$Predicted*12.96)
predD2 = as.vector(pred2$Predicted*12.96)
predD3 = as.vector(pred3$Predicted*12.96)
predD4 = as.vector(pred4$Predicted*12.96)
predD5 = as.vector(pred5$Predicted*12.96)
predD6 = as.vector(pred6$Predicted*12.96)
predD7 = as.vector(pred7$Predicted*12.96)
predD8 = as.vector(pred8$Predicted*12.96)
predD9 = as.vector(pred9$Predicted*12.96)
predD10 = as.vector(pred10$Predicted*12.96)
predD11 = as.vector(pred11$Predicted*12.96)
predD12 = as.vector(pred12$Predicted*12.96)
predD13 = as.vector(pred13$Predicted*12.96)
predD14 = as.vector(pred14$Predicted*12.96)
predD15 = as.vector(pred15$Predicted*12.96)
predD16 = as.vector(pred16$Predicted*12.96)
predD17 = as.vector(pred17$Predicted*12.96)
predD18 = as.vector(pred18$Predicted*12.96)
predD19 = as.vector(pred19$Predicted*12.96)
predD20 = as.vector(pred20$Predicted*12.96)
predD21 = as.vector(pred21$Predicted*12.96)
predD22 = as.vector(pred22$Predicted*12.96)
predD23 = as.vector(pred23$Predicted*12.96)
predD24 = as.vector(pred24$Predicted*12.96)
predD25 = as.vector(pred25$Predicted*12.96)
predD26 = as.vector(pred26$Predicted*12.96)
```

```
predD27 = as.vector(pred27$Predicted*12.96)
predD28 = as.vector(pred28$Predicted*12.96)
predD29 = as.vector(pred29$Predicted*12.96)
predD30 = as.vector(pred30$Predicted*12.96)
predD31 = as.vector(pred31$Predicted*12.96)
predD32 = as.vector(pred32$Predicted*12.96)
predD33 = as.vector(pred33$Predicted*12.96)
predD34 = as.vector(pred34$Predicted*12.96)

# Total population size estimates (lek abundance). #
POP1 = sum(predD1)
POP2 = sum(predD2)
POP3 = sum(predD3)
POP4 = sum(predD4)
POP5 = sum(predD5)
POP6 = sum(predD6)
POP7 = sum(predD7)
POP8 = sum(predD8)
POP9 = sum(predD9)
POP10 = sum(predD10)
POP11 = sum(predD11)
POP12 = sum(predD12)
POP13 = sum(predD13)
POP14 = sum(predD14)
POP15 = sum(predD15)
POP16 = sum(predD16)
POP17 = sum(predD17)
POP18 = sum(predD18)
POP19 = sum(predD19)
POP20 = sum(predD20)
POP21 = sum(predD21)
POP22 = sum(predD22)
POP23 = sum(predD23)
POP24 = sum(predD24)
POP25 = sum(predD25)
POP26 = sum(predD26)
POP27 = sum(predD27)
POP28 = sum(predD28)
POP29 = sum(predD29)
POP30 = sum(predD30)
POP31 = sum(predD31)
POP32 = sum(predD32)
POP33 = sum(predD33)
```

```
POP34 = sum(predD34)

# Make a data frame of the needed variables, then do for all models. #
XGRID1 =
    cbind(rep(1,nrow(GRID)),GRID$RESHRUB,GRID$RESHRUB2,GRID$RETRA
    NSM)
XGRID2 = cbind(rep(1,nrow(GRID)),GRID$RESHRUB,GRID$RESHRUB2)
XGRID3 = cbind(rep(1,nrow(GRID)),GRID$GRAIN)
XGRID4 = cbind(rep(1,nrow(GRID)),GRID$AGP)
XGRID5 = cbind(rep(1,nrow(GRID)),GRID$ASP)
XGRID6 = cbind(rep(1,nrow(GRID)),GRID$EDGE)
XGRID7 =
    cbind(rep(1,nrow(GRID)),GRID$SHRUB,GRID$RESHRUB2,GRID$GRAIN)
XGRID8 =
    cbind(rep(1,nrow(GRID)),GRID$RESHRUB,GRID$RESHRUB2,GRID$EDGE)
XGRID9 =
    cbind(rep(1,nrow(GRID)),GRID$RESHRUB,GRID$RESHRUB2,GRID$GRAIN
    ,GRID$EDGE)
XGRID10 = cbind(rep(1,nrow(GRID)),GRID$GRAIN,GRID$EDGE)
XGRID11 = cbind(rep(1,nrow(GRID)),GRID$AGP,GRID$EDGE)
XGRID12 = cbind(rep(1,nrow(GRID)),GRID$ASP,GRID$EDGE)
XGRID13 = cbind(rep(1,nrow(GRID)),GRID$AGP,GRID$GRAIN)
XGRID14 = cbind(rep(1,nrow(GRID)),GRID$AGP,GRID$GRAIN,GRID$EDGE)
XGRID15 = cbind(rep(1,nrow(GRID)),GRID$ASP,GRID$GRAIN,GRID$EDGE)
XGRID16 = cbind(rep(1,nrow(GRID)),GRID$ASP,GRID$GRAIN)
XGRID17 = cbind(rep(1,nrow(GRID)),GRID$REDIRT)
XGRID18 = cbind(rep(1,nrow(GRID)),GRID$HWY)
XGRID19 = cbind(rep(1,nrow(GRID)),GRID$ROADS)
XGRID20 = cbind(rep(1,nrow(GRID)),GRID$RETRANSM)
XGRID21 = cbind(rep(1,nrow(GRID)),GRID$WELL)
XGRID22 = cbind(rep(1,nrow(GRID)),GRID$RETRANSM,GRID$WELL)
XGRID23 = cbind(rep(1,nrow(GRID)),GRID$REDIRT,GRID$RETRANSM)
XGRID24 =
    cbind(rep(1,nrow(GRID)),GRID$REGRASS,GRID$REGRASS2,GRID$GRAIN)
XGRID25 =
    cbind(rep(1,nrow(GRID)),GRID$REGRASS,GRID$REGRASS2,GRID$GRAIN,
    GRID$EDGE)
XGRID26 =
    cbind(rep(1,nrow(GRID)),GRID$REGRASS,GRID$REGRASS2,GRID$EDGE)
XGRID27 = cbind(rep(1,nrow(GRID)))
XGRID28 = cbind(rep(1,nrow(GRID)),GRID$HWY,GRID$REDIRT)
XGRID29 = cbind(rep(1,nrow(GRID)),GRID$REGRASS,GRID$REGRASS2)
```

```
XGRID30 =
        cbind(rep(1,nrow(GRID)),GRID$RESHRUB,GRID$RESHRUB2,GRID$REDIR
        T)
XGRID31 =
        cbind(rep(1,nrow(GRID)),GRID$RESHRUB,GRID$RESHRUB2,GRID$REDIR
        T,GRID$RETRANSM)
XGRID32 =
        cbind(rep(1,nrow(GRID)),GRID$RESHRUB,GRID$RESHRUB2,GRID$HWY,
        GRID$REDIRT)
XGRID33 =
        cbind(rep(1,nrow(GRID)),GRID$RESHRUB,GRID$RESHRUB2,GRID$HWY,
        GRID$REDIRT,GRID$RETRANSM)
XGRID34 =
        cbind(rep(1,nrow(GRID)),GRID$RETRANSM,GRID$HWY,GRID$REDIRT)

#A function to do parametric bootstrap of the total population size to determine variance
        for all models. #
gridN1 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(RESHRUB)","lam(RESHRUB2)","lam(RETRANSM)")]
 sum(12.96*exp(XGRID1%*%(beta)))
}

gridN2 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(RESHRUB)","lam(RESHRUB2)")]
 sum(12.96*exp(XGRID2%*%(beta)))
}

gridN3 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(GRAIN)")]
 sum(12.96*exp(XGRID3%*%(beta)))
}

gridN4 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(AGP)")]
 sum(12.96*exp(XGRID4%*%(beta)))
}

gridN5 = function(fm) {
 beta = coef(fm)
```

```
 beta = beta[c("lam(Int)","lam(ASP)")]
 sum(12.96*exp(XGRID5%*%(beta)))
}

gridN6 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(EDGE)")]
 sum(12.96*exp(XGRID6%*%(beta)))
}

gridN7 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(RESHRUB)","lam(RESHRUB2)","lam(GRAIN)")]
 sum(12.96*exp(XGRID7%*%(beta)))
}

gridN8 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(RESHRUB)","lam(RESHRUB2)","lam(EDGE)")]
 sum(12.96*exp(XGRID8%*%(beta)))
}

gridN9 = function(fm) {
 beta = coef(fm)
 beta =
        beta[c("lam(Int)","lam(RESHRUB)","lam(RESHRUB2)","lam(GRAIN)","lam(E
        DGE)")]
 sum(12.96*exp(XGRID9%*%(beta)))
}

gridN10 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(GRAIN)","lam(EDGE)")]
 sum(12.96*exp(XGRID10%*%(beta)))
}

gridN11 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(AGP)","lam(EDGE)")]
 sum(12.96*exp(XGRID11%*%(beta)))
}

gridN12 = function(fm) {
```

```
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(ASP)","lam(EDGE)")]
 sum(12.96*exp(XGRID12%*%(beta)))
}

gridN13 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(AGP)","lam(GRAIN)")]
 sum(12.96*exp(XGRID13%*%(beta)))
}

gridN14 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(AGP)","lam(GRAIN)","lam(EDGE)")]
 sum(12.96*exp(XGRID14%*%(beta)))
}

gridN15 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(ASP)","lam(GRAIN)","lam(EDGE)")]
 sum(12.96*exp(XGRID15%*%(beta)))
}

gridN16 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(ASP)","lam(GRAIN)")]
 sum(12.96*exp(XGRID16%*%(beta)))
}

gridN17 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(REDIRT)")]
 sum(12.96*exp(XGRID17%*%(beta)))
}

gridN18 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(HWY)")]
 sum(12.96*exp(XGRID18%*%(beta)))
}

gridN19 = function(fm) {
 beta = coef(fm)
```

```
 beta = beta[c("lam(Int)","lam(ROADS)")]
 sum(12.96*exp(XGRID19%*%(beta)))
}

gridN20 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(RETRANSM)")]
 sum(12.96*exp(XGRID20%*%(beta)))
}

gridN21 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(WELL)")]
 sum(12.96*exp(XGRID21%*%(beta)))
}

gridN22 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(RETRANSM)","lam(WELL)")]
 sum(12.96*exp(XGRID22%*%(beta)))
}

gridN23 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(REDIRT)","lam(RETRANSM)")]
 sum(12.96*exp(XGRID23%*%(beta)))
}

gridN24 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(REGRASS)","lam(REGRASS2)","lam(GRAIN)")]
 sum(12.96*exp(XGRID24%*%(beta)))
}

gridN25 = function(fm) {
 beta = coef(fm)
 beta =
      beta[c("lam(Int)","lam(REGRASS)","lam(REGRASS2)","lam(GRAIN)","lam(E
      DGE)")]
 sum(12.96*exp(XGRID25%*%(beta)))
}

gridN26 = function(fm) {
```

```
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(REGRASS)","lam(REGRASS2)","lam(EDGE)")]
 sum(12.96*exp(XGRID26%*%(beta)))
}

gridN27 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)")]
 sum(12.96*exp(XGRID27%*%(beta)))
}

gridN28 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(HWY)","lam(REDIRT)")]
 sum(12.96*exp(XGRID28%*%(beta)))
}

gridN29 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(REGRASS)","lam(REGRASS2)")]
 sum(12.96*exp(XGRID29%*%(beta)))
}

gridN30 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(RESHRUB)","lam(RESHRUB2)","lam(REDIRT)")]
 sum(12.96*exp(XGRID30%*%(beta)))
}

gridN31 = function(fm) {
 beta = coef(fm)
 beta =
      beta[c("lam(Int)","lam(RESHRUB)","lam(RESHRUB2)","lam(REDIRT)","lam(
      RETRANSM)")]
 sum(12.96*exp(XGRID31%*%(beta)))
}

gridN32 = function(fm) {
 beta = coef(fm)
 beta =
      beta[c("lam(Int)","lam(RESHRUB)","lam(RESHRUB2)","lam(HWY)","lam(RE
      DIRT)")]
 sum(12.96*exp(XGRID32%*%(beta)))
```

```
}

gridN33 = function(fm) {
 beta = coef(fm)
 beta =
        beta[c("lam(Int)","lam(RESHRUB)","lam(RESHRUB2)","lam(HWY)","lam(RE
        DIRT)","lam(RETRANSM)")]
 sum(12.96*exp(XGRID33%*%(beta)))
}

gridN34 = function(fm) {
 beta = coef(fm)
 beta = beta[c("lam(Int)","lam(RETRANSM)","lam(HWY)","lam(REDIRT)")]
 sum(12.96*exp(XGRID34%*%(beta)))
}

# Do a parametric bootstrap to estimate var(N) for each model; it takes awhile for each
        model. #
pnb.pop1 = parboot(hn_shrub_transm_km2,gridN1,nsim=1000,report=2)
pnb.pop2 = parboot(hn_shrub_km2,gridN2,nsim=1000,report=2)
pnb.pop3 = parboot(hn_grain_km2,gridN3,nsim=1000,report=2)
pnb.pop4 = parboot(hn_agp_km2,gridN4,nsim=1000,report=2)
pnb.pop5 = parboot(hn_asp_km2,gridN5,nsim=1000,report=2)
pnb.pop6 = parboot(hn_edge_km2,gridN6,nsim=1000,report=2)
pnb.pop7 = parboot(hn_shrub_grain_km2,gridN7,nsim=1000,report=2)
pnb.pop8 = parboot(hn_shrub_edge_km2,gridN8,nsim=1000,report=2)
pnb.pop9 = parboot(hn_shrub_grain_edge_km2,gridN9,nsim=1000,report=2)
pnb.pop10 = parboot(hn_grain_edge_km2,gridN10,nsim=1000,report=2)
pnb.pop11 = parboot(hn_agp_edge_km2,gridN11,nsim=1000,report=2)
pnb.pop12 = parboot(hn_asp_edge_km2,gridN12,nsim=1000,report=2)
pnb.pop13 = parboot(hn_agp_grain_km2,gridN13,nsim=1000,report=2)
pnb.pop14 = parboot(hn_agp_grain_edge_km2,gridN14,nsim=1000,report=2)
pnb.pop15 = parboot(hn_asp_grain_edge_km2,gridN15,nsim=1000,report=2)
pnb.pop16 = parboot(hn_asp_grain_km2,gridN16,nsim=1000,report=2)
pnb.pop17 = parboot(hn_dirt_km2,gridN17,nsim=1000,report=2)
pnb.pop18 = parboot(hn_hwy_km2,gridN18,nsim=1000,report=2)
pnb.pop19 = parboot(hn_roads_km2,gridN19,nsim=1000,report=2)
pnb.pop20 = parboot(hn_transm_km2,gridN20,nsim=1000,report=2)
pnb.pop21 = parboot(hn_well_km2,gridN21,nsim=1000,report=2)
pnb.pop22 = parboot(hn_transm_well_km2,gridN22,nsim=1000,report=2)
pnb.pop23 = parboot(hn_dirt_transm_km2,gridN23,nsim=1000,report=2)
pnb.pop24 = parboot(hn_grass_grain_km2,gridN24,nsim=1000,report=2)
pnb.pop25 = parboot(hn_grass_grain_edge_km2,gridN25,nsim=1000,report=2)
```

```
pnb.pop26 = parboot(hn_grass_edge_km2,gridN26,nsim=1000,report=2)
pnb.pop27 = parboot(hn_km2,gridN27,nsim=1000,report=2)
pnb.pop28 = parboot(hn_hwy_dirt_km2,gridN28,nsim=1000,report=2)
pnb.pop29 = parboot(hn_grass_km2,gridN29,nsim=1000,report=2)
pnb.pop30 = parboot(hn_shrub_dirt_km2,gridN30,nsim=1000,report=2)
pnb.pop31 = parboot(hn_shrub_dirt_transm_km2,gridN31,nsim=1000,report=2)
pnb.pop32 = parboot(hn_shrub_hwy_dirt_km2,gridN32,nsim=1000,report=2)
pnb.pop33 = parboot(hn_shrub_hwy_dirt_transm_km2,gridN33,nsim=1000,report=2)
pnb.pop34 = parboot(hn_transm_hwy_dirt_km2,gridN34,nsim=1000,report=2)

# Show the bootstrap results for top model. #
pnb.pop32
plot(pnb.pop32)

# Get the parboot SDs and CVs for all models. #
pop1.boots = attr(pnb.pop1,"t.star")
sd.boot1 = apply(pop1.boots,2,sd)
cv.boot1 = sd.boot1/POP1

pop2.boots = attr(pnb.pop2,"t.star")
sd.boot2 = apply(pop2.boots,2,sd)
cv.boot2 = sd.boot2/POP2

pop3.boots = attr(pnb.pop3,"t.star")
sd.boot3 = apply(pop3.boots,2,sd)
cv.boot3 = sd.boot3/POP3

pop4.boots = attr(pnb.pop4,"t.star")
sd.boot4 = apply(pop4.boots,2,sd)
cv.boot4 = sd.boot4/POP4

pop5.boots = attr(pnb.pop5,"t.star")
sd.boot5 = apply(pop5.boots,2,sd)
cv.boot5 = sd.boot5/POP5

pop6.boots = attr(pnb.pop6,"t.star")
sd.boot6 = apply(pop6.boots,2,sd)
cv.boot6 = sd.boot6/POP6

pop7.boots = attr(pnb.pop7,"t.star")
sd.boot7 = apply(pop7.boots,2,sd)
cv.boot7 = sd.boot7/POP7
```

```
pop8.boots = attr(pnb.pop8,"t.star")
sd.boot8 = apply(pop8.boots,2,sd)
cv.boot8 = sd.boot8/POP8

pop9.boots = attr(pnb.pop9,"t.star")
sd.boot9 = apply(pop9.boots,2,sd)
cv.boot9 = sd.boot9/POP9
pop10.boots = attr(pnb.pop10,"t.star")
sd.boot10 = apply(pop10.boots,2,sd)
cv.boot10 = sd.boot10/POP10

pop11.boots = attr(pnb.pop11,"t.star")
sd.boot11 = apply(pop11.boots,2,sd)
cv.boot11 = sd.boot11/POP11

pop12.boots = attr(pnb.pop12,"t.star")
sd.boot12 = apply(pop12.boots,2,sd)
cv.boot12 = sd.boot12/POP12

pop13.boots = attr(pnb.pop13,"t.star")
sd.boot13 = apply(pop13.boots,2,sd)
cv.boot13 = sd.boot13/POP13

pop14.boots = attr(pnb.pop14,"t.star")
sd.boot14 = apply(pop14.boots,2,sd)
cv.boot14 = sd.boot14/POP14

pop15.boots = attr(pnb.pop15,"t.star")
sd.boot15 = apply(pop15.boots,2,sd)
cv.boot15 = sd.boot15/POP15

pop16.boots = attr(pnb.pop16,"t.star")
sd.boot16 = apply(pop16.boots,2,sd)
cv.boot16 = sd.boot16/POP16

pop17.boots = attr(pnb.pop17,"t.star")
sd.boot17 = apply(pop17.boots,2,sd)
cv.boot17 = sd.boot17/POP17

pop18.boots = attr(pnb.pop18,"t.star")
sd.boot18 = apply(pop18.boots,2,sd)
cv.boot18 = sd.boot18/POP18
```

```
pop19.boots = attr(pnb.pop19,"t.star")
sd.boot19 = apply(pop19.boots,2,sd)
cv.boot19 = sd.boot19/POP19

pop20.boots = attr(pnb.pop20,"t.star")
sd.boot20 = apply(pop20.boots,2,sd)
cv.boot20 = sd.boot20/POP20

pop21.boots = attr(pnb.pop21,"t.star")
sd.boot21 = apply(pop21.boots,2,sd)
cv.boot21 = sd.boot21/POP21

pop22.boots = attr(pnb.pop22,"t.star")
sd.boot22 = apply(pop22.boots,2,sd)
cv.boot22 = sd.boot22/POP22

pop23.boots = attr(pnb.pop23,"t.star")
sd.boot23 = apply(pop23.boots,2,sd)
cv.boot23 = sd.boot23/POP23

pop24.boots = attr(pnb.pop24,"t.star")
sd.boot24 = apply(pop24.boots,2,sd)
cv.boot24 = sd.boot24/POP24

pop25.boots = attr(pnb.pop25,"t.star")
sd.boot25 = apply(pop25.boots,2,sd)
cv.boot25 = sd.boot25/POP25

pop26.boots = attr(pnb.pop26,"t.star")
sd.boot26 = apply(pop26.boots,2,sd)
cv.boot26 = sd.boot26/POP26

pop27.boots = attr(pnb.pop27,"t.star")
sd.boot27 = apply(pop27.boots,2,sd)
cv.boot27 = sd.boot27/POP27

pop28.boots = attr(pnb.pop28,"t.star")
sd.boot28 = apply(pop28.boots,2,sd)
cv.boot28 = sd.boot28/POP28

pop29.boots = attr(pnb.pop29,"t.star")
sd.boot29 = apply(pop29.boots,2,sd)
cv.boot29 = sd.boot29/POP29
```

```
pop30.boots = attr(pnb.pop30,"t.star")
sd.boot30 = apply(pop30.boots,2,sd)
cv.boot30 = sd.boot30/POP30

pop31.boots = attr(pnb.pop31,"t.star")
sd.boot31 = apply(pop31.boots,2,sd)
cv.boot31 = sd.boot31/POP31

pop32.boots = attr(pnb.pop32,"t.star")
sd.boot32 = apply(pop32.boots,2,sd)
cv.boot32 = sd.boot32/POP32

pop33.boots = attr(pnb.pop33,"t.star")
sd.boot33 = apply(pop33.boots,2,sd)
cv.boot33 = sd.boot33/POP33

pop34.boots = attr(pnb.pop34,"t.star")
sd.boot34 = apply(pop34.boots,2,sd)
cv.boot34 = sd.boot34/POP34

# Final Estimates for top model (model32), shrub+hwy+dirt model. #
POP32
sd.boot32
cv.boot32

# Export pred32 frame to a CSV file and multiply predicted values and upper and lower
        CI's by 12.96 and use delta method for SE. #
write.table(pred32,file="C:/
        prediction2.csv",append=FALSE,sep=",",row.names=FALSE,col.names=TRUE)

#Combine Grid file with prediction file and add to GIS, project, and save as data layer;
        then join with the quadrat shapefile to make density map for the quadrats.#

# Get covariate values to make a graph predicting lek density. #
GRAPH = read.table("C:/graph.csv",header=TRUE,sep=",")
GRAPH$REDIRT = (GRAPH$DIRT-mean.dirt)/std.dirt
GRAPH$RESHRUB = (GRAPH$SHRUB-mean.shrub)/std.shrub
GRAPH$RESHRUB2 = GRAPH$RESHRUB*GRAPH$RESHRUB

# Predict density values for graph. #
pred.graph = predict(topfits, type="state", newdata=GRAPH, appendData=TRUE)
pred.graph$predicted.abund = pred.graph$Predicted*12.96
```

```
# Export pred.graph to a csv file. #
write.table(pred.graph,file="C:/predgraph2.csv",append=FALSE,sep=",",row.names=FALSE,col.names=TRUE)
```

APPENDIX C

PREDICTED LEK DENSITY MAPS

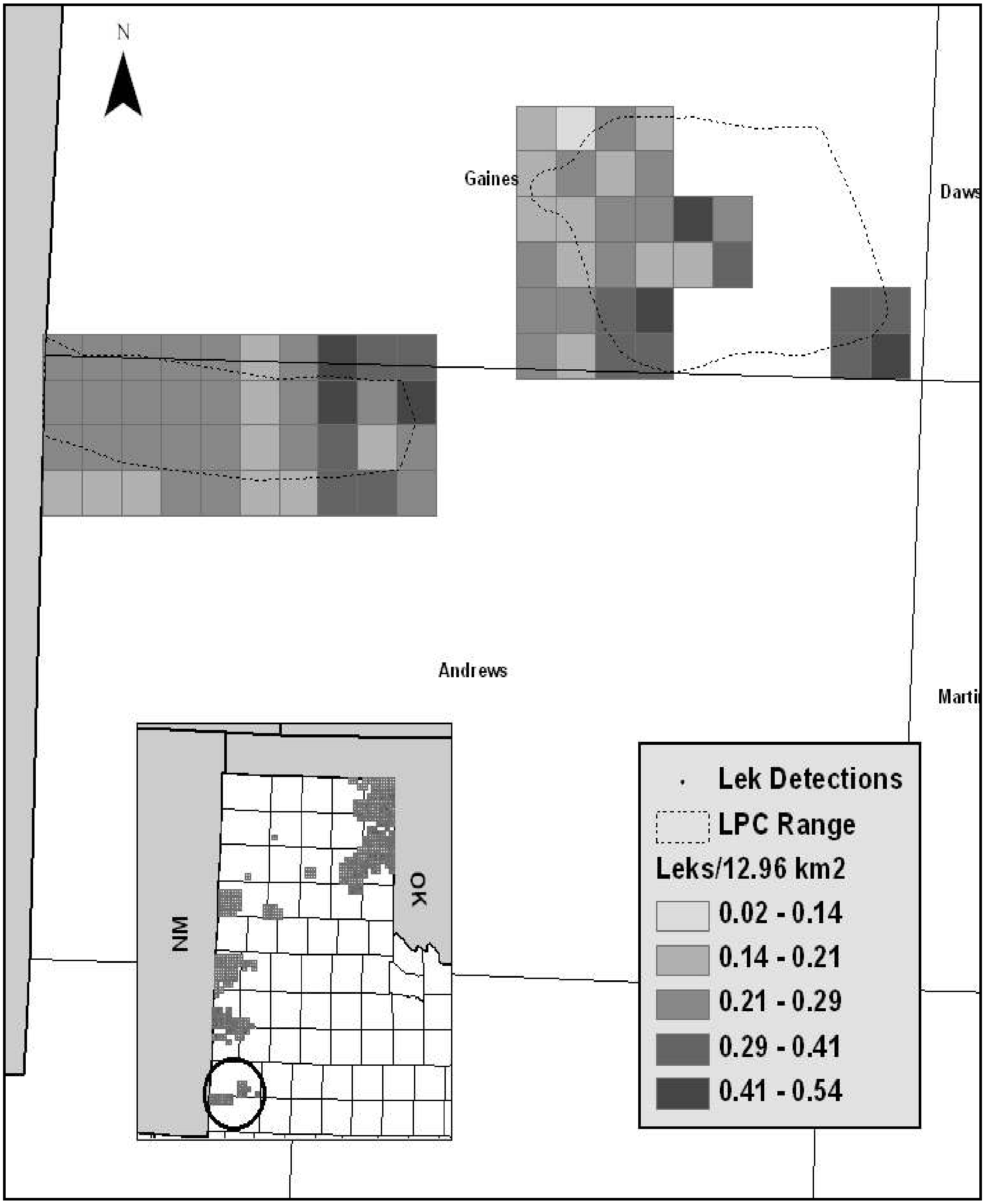

Figure C1. Predicted lesser prairie-chicken (LPC) lek density for 12.96 km^2 quadrats in Andrews and Gaines counties, Texas, USA. Predictions based on a hierarchical distance sampling model of percent shrubland patches and paved and unpaved road densities (km/km^2).

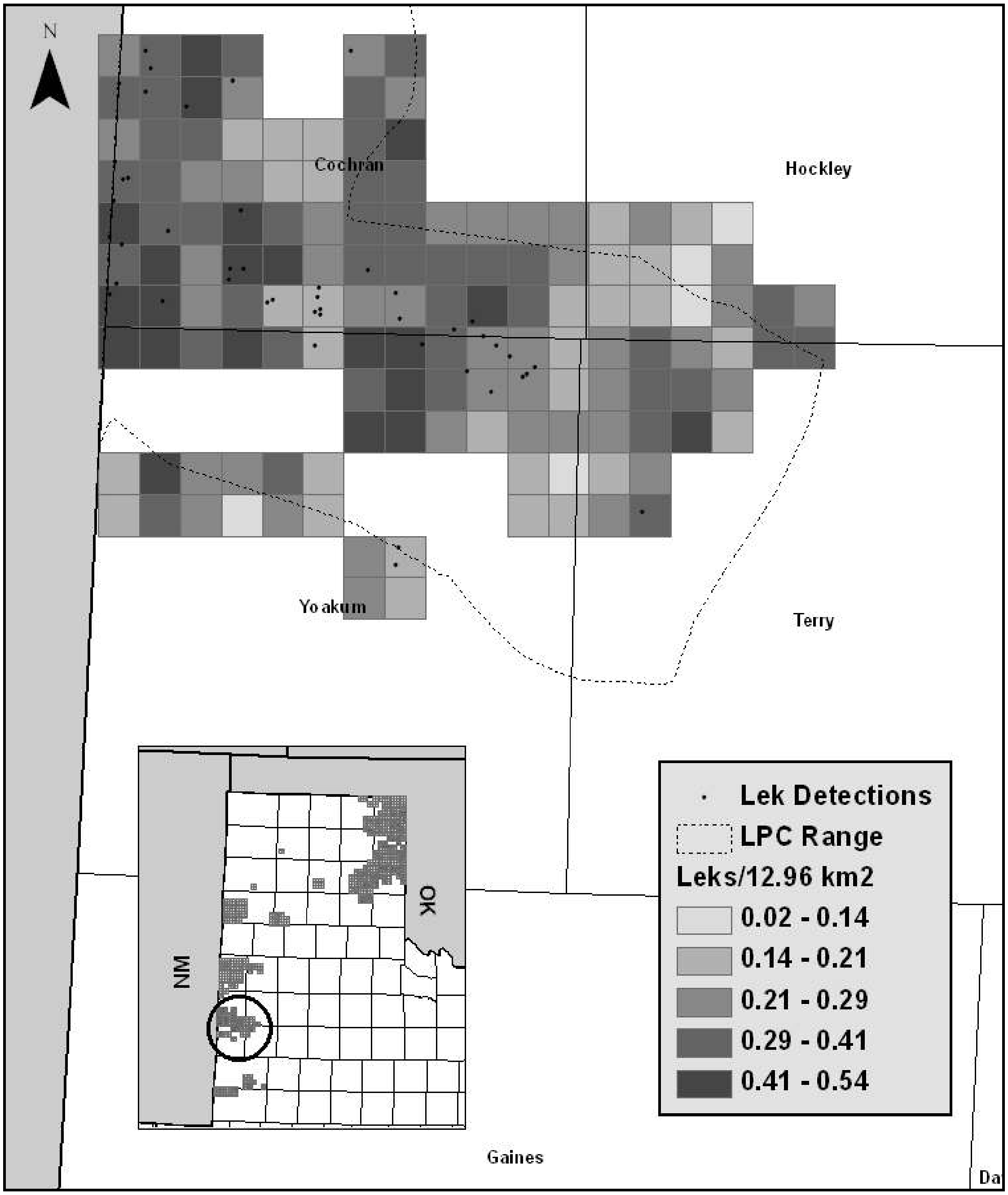

Figure C2. Predicted lesser prairie-chicken (LPC) lek density for 12.96 km^2 quadrats in Cochran, Hockley, Terry, and Yoakum counties, Texas, USA. Predictions based on a hierarchical distance sampling model of percent shrubland patches and paved and unpaved road densities (km/km^2).

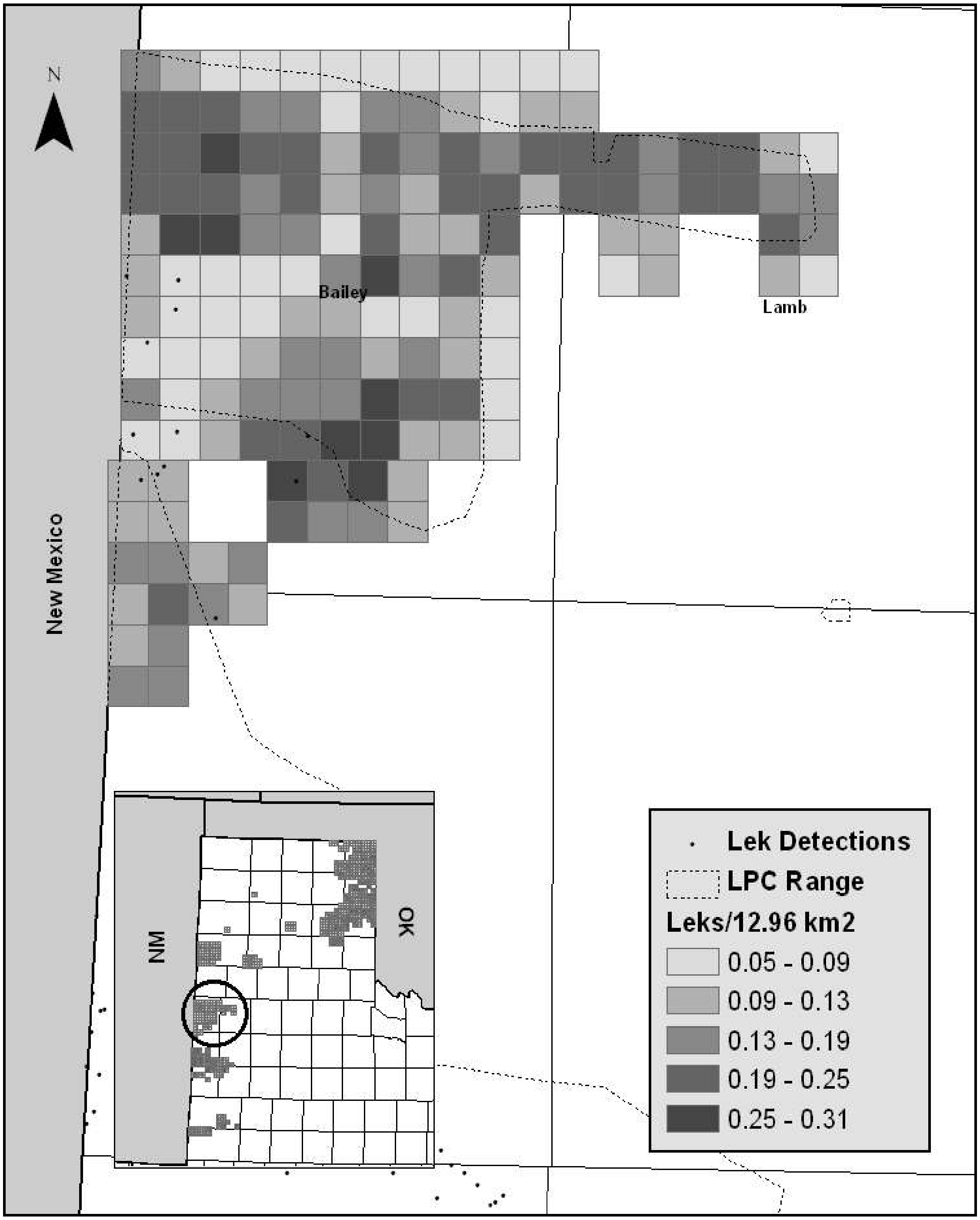

Figure C3. Predicted lesser prairie-chicken (LPC) lek density for 12.96 km^2 quadrats in Bailey, Cochran, and Lamb counties, Texas, USA. Predictions based on a hierarchical distance sampling model of percent shrubland patches and paved and unpaved road densities (km/km^2).

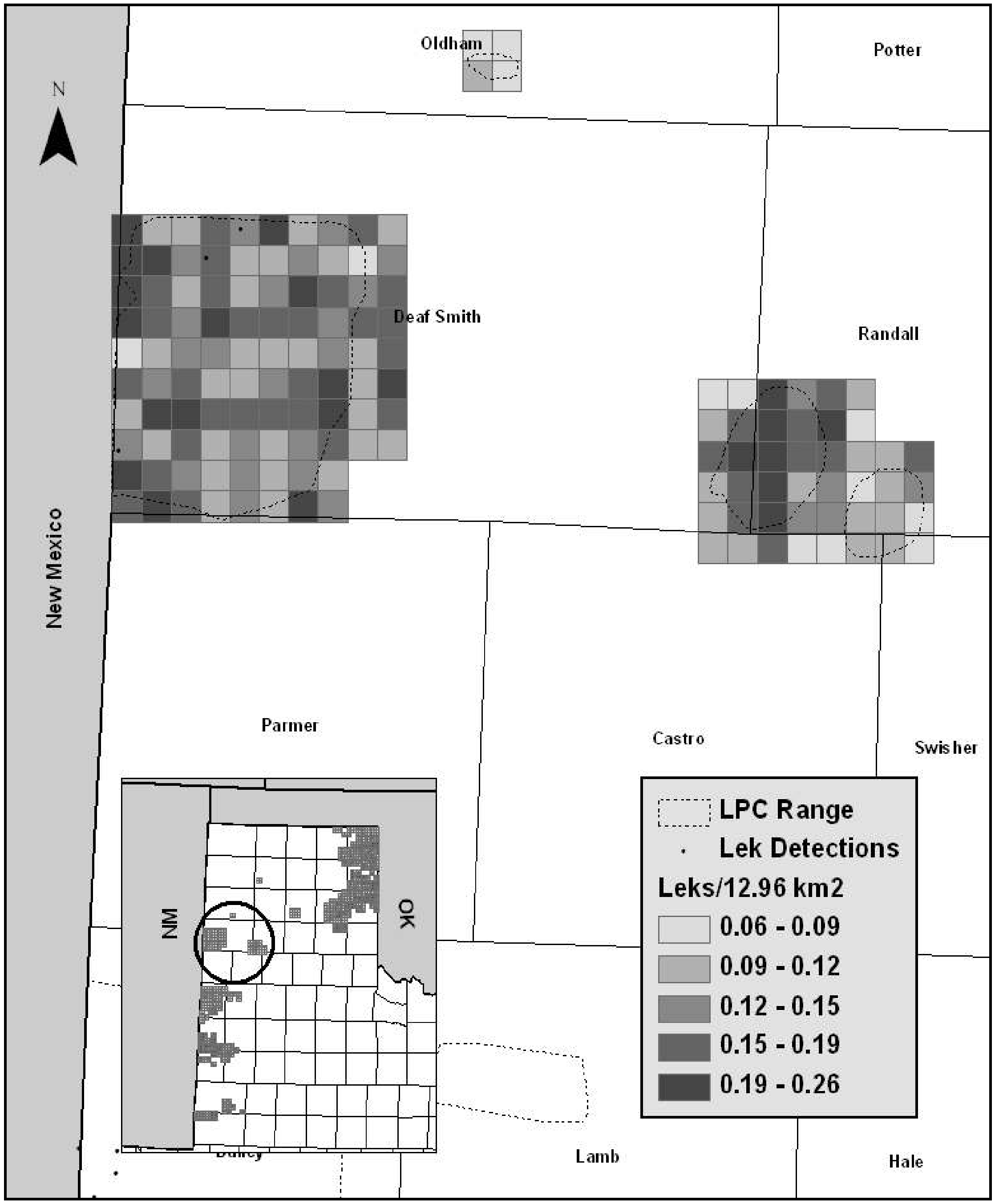

Figure C4. Predicted lesser prairie-chicken (LPC) lek density for 12.96 km^2 quadrats in Castro, Deaf Smith, Oldham, Randall, and Swisher counties, Texas, USA. Predictions based on a hierarchical distance sampling model of percent shrubland patches and paved and unpaved road densities (km/km^2).

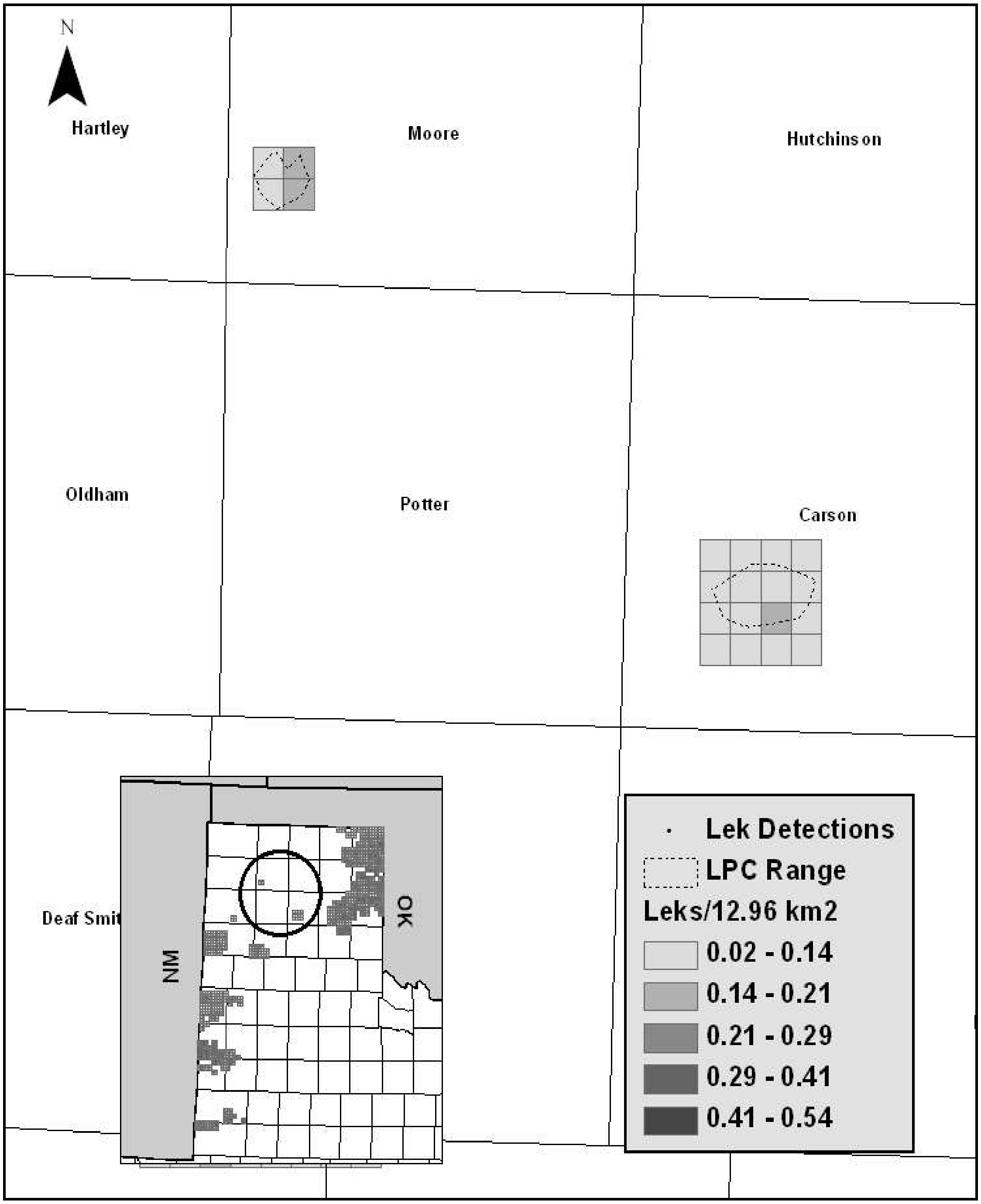

Figure C5. Predicted lesser prairie-chicken (LPC) lek density for 12.96 km^2 quadrats in Carson and Moore counties, Texas, USA. Predictions based on a hierarchical distance sampling model of percent shrubland patches and paved and unpaved road densities (km/km^2).

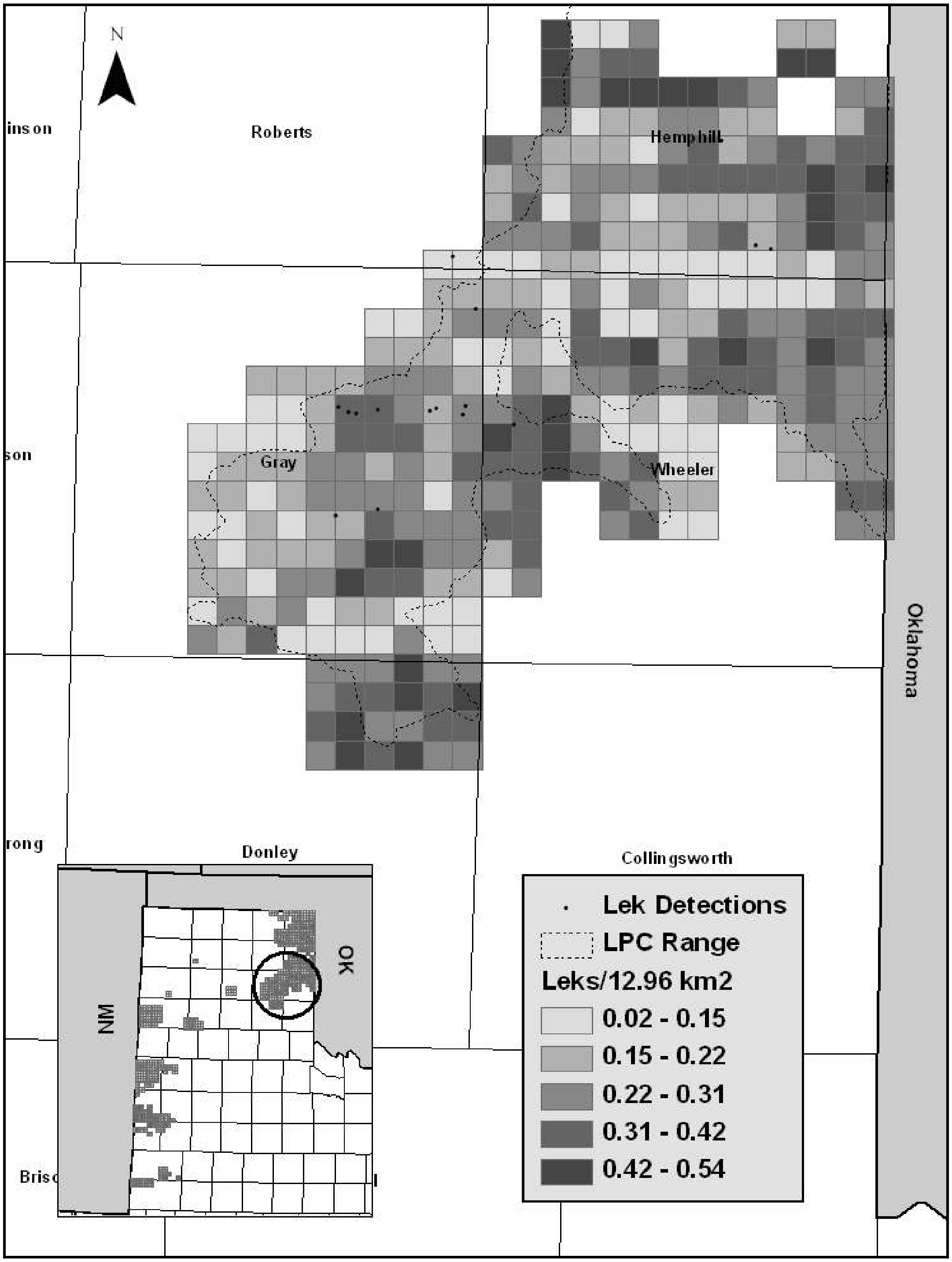

Figure C6. Predicted lesser prairie-chicken (LPC) lek density for 12.96 km^2 quadrats in Donley, Gray, Hemphill, Roberts, and Wheeler counties, Texas, USA. Predictions based on a hierarchical distance sampling model of percent shrubland patches and paved and unpaved road densities (km/km^2).

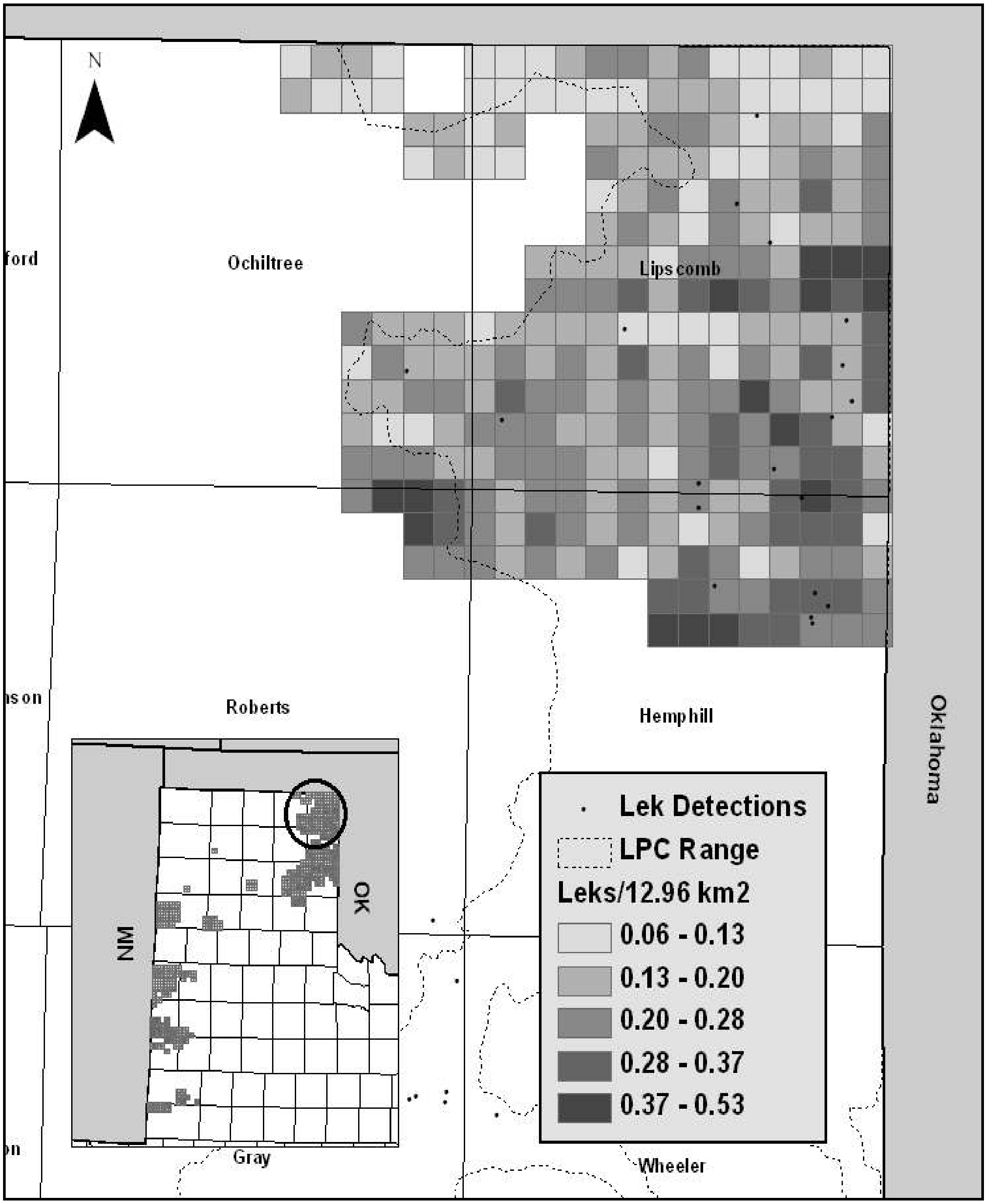

Figure C7. Predicted lesser prairie-chicken (LPC) lek density for 12.96 km^2 quadrats in Hemphill, Lipscomb, Ochiltree, and Roberts counties, Texas, USA. Predictions based on a hierarchical distance sampling model of percent shrubland patches and paved and unpaved road densities (km/km^2).