ABSTRACT

DZIWULSKI, KARA ELIZABETH. Habitat Use and Survival of Eastern Cottontails (*Sylvilagus floridanus*) on Christmas Tree Farms, and the Utility of Expert Knowledge in Informing Management Decisions on Human-modified Landscapes. (Under the direction of Dr. Jaime Collazo).

Agricultural production is a driving force behind the alteration of global natural landscapes. Despite its prevalence, little is currently known about how agricultural crop lands are utilized by most wildlife species. Christmas trees are an example of a specialty crop whose ecological impacts are largely unknown. Understanding the challenges and opportunities for biodiversity conservation on such landscapes has been hampered by the costs of collecting essential ecological data. Recently, expert knowledge has been advanced as a tool to fill knowledge gaps about systems and species that are understudied. Expert knowledge has the potential to serve as a standardized way to estimate and compare ecological impacts, in turn, promoting conservation and informing management decisions. The objectives of this study are to (1) increase knowledge about habitat selection and survival of eastern cottontails (*Sylvilagus flordanus*) on an understudied agricultural system: Christmas tree farms in western North Carolina, while (2) simultaneously testing the utility of expert knowledge by comparing expert prior predictions of cottontail habitat selection on farms to uniformed priors, both coupled with empirical data.

We radio-tracked 57 eastern cottontails on 5 Christmas tree farms March 15 to June 30, 2014 to 2015. Animal locations were collected twice-daily four days a week during crepuscular hours (6-10 am & 5-9 pm), with one mid-day location (6-2 pm) taken on the 5th day to capture potential resting locations. We characterized habitat occurring inside and outside farms, for individuals with ≥ 30 telemetry locations calculated 95% fixed kernel home ranges. Habitat selection was assessed at the 3rd order using a Bayesian mixed effects discrete choice model.

We used known-fates analysis to calculate weekly study-period survival, and extrapolated estimates of breeding season and annual survival rates. We used an independent, experienced elicitator to collect expert knowledge from 3 experts of mammalian ecology on cottontail habitat use and convert their knowledge into priors. We then examined parameter estimates and predictions resulting from Bayesian analysis incorporating informative (expert) priors versus uninformative priors. We conducted a five-fold cross validation to compare if models run with informative or uninformative priors better fit the empirical data.

We found the average cottontail home range size to be 6.23 ha with males averaging 9.17 ha and females 3.39 ha. Cottontails selected habitat in proportion to its availability, with males avoiding fields containing extra-small Christmas trees. The probability of selecting a Christmas tree field increased as the proportion of herbaceous cover increased. Weekly study-period survival was 0.98 ± 0.01, with breeding season survival estimated at 0.55 ± 0.17 (Mar-Sept) and annual survival at 0.35 ± 0.18. Posteriors incorporating expert priors tended to greatly vary from posteriors derived from the non-informative priors. Mean squared errors produced by the cross validation were smaller for models incorporating non-informative priors in comparison to the same models run with expert priors, indicating expert knowledge did not improve prediction of cottontail occurrence on Christmas tree farms.

This project expands knowledge of eastern cottontail ecology on Christmas tree farms and suggests these agricultural lands provide suitable habitat for eastern cottontails. It is also explicitly evaluates the utility of expert knowledge to guide wildlife management in human-modified habitats such as Christmas tree farms in North Carolina. We stress the importance of collecting expert knowledge data using a standardized elicitation protocol that minimizes expert subjectivity, followed by quantitative assessments as the one described in this study.

Habitat Use and Survival of Eastern Cottontails (*Sylvilagus floridanus*) on Christmas Tree Farms, and the Utility of Expert Knowledge in Informing Management Decisions on Human-modified Landscapes.

by
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APPROVED BY:

Dr. Jaime Collazo Committee Chair	Dr. David Cobb
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DEDICATION

To my parents, Marge and Kevin Dziwulski, who have continuously fostered and supported my pursuits in wildlife biology.

BIOGRAPHY

Kara Dziwulski grew up in Raleigh, North Carolina where her inherent interest in wildlife was fostered during her six years volunteering as a junior curator with the North Carolina Museum of Natural Sciences. In 2011, she received a BS in Fisheries, Wildlife and Conservation Biology from North Carolina State University after also completing a semester of undergraduate studies at the University of Alaska Fairbanks.

Upon graduation, Kara spent a year gaining research experience working various biological technician jobs. One experience in particular led her to conduct avian research in Puerto Rico under Dr. Jaime Collazo whom she later accepted a graduate position with within the NC Fisheries and Wildlife Cooperative Research Unit at NCSU. During her time in graduate school she was selected as a Pathways Biological Intern for the US Fish and Wildlife Service and spent her final years in graduate school working jointly for NCSU and the USFWS Ecological Services Office in Asheville, North Carolina.

Upon completion of her masters, Kara plans to continue her career with the USFWS in their International Affairs Office to exercise her passion for national and international wildlife conservation and management.

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There might be an “I” in “thesis” but my masters project was far from an individual accomplishment. Many people greatly contributed to the success of this project and deserve endless recognition and appreciation for the roles they played in making it possible.

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This project would not have been possible without the instrumental assistance I received from NC Cooperative Extension employees: Brad Edwards, Travis Birdsell, Dr. Jill Sidebottom, Jim Hamilton, and Jeff Owens, who helped me establish relationships with local Christmas tree producers, and provided crash-courses on Christmas tree management practices. In particular, I need to acknowledge Brad for the hours he spent touring potential farms, helping us out of sticky situations, and assisting with radio telemetry. This project would not have been as successful as it was without his help, and I cannot thank him enough for the hospitality and friendship he showed me during my time in the mountains!

Gaining insight on the Christmas tree industry in North Carolina and building relationships with the local Christmas tree producers who understand it so intimately, was a very special aspect of conducting this research. I will always be indebted to the following Christmas tree farmers who trusted me enough to conduct research on their farms: Wiley Gimlin, Ken Gardner, Charles Sturgill, Don Tucker, Joe Freeman, Buddy Deal, and Joey Clawson. Thank you for embracing me into your community, and exposing me to a part of my home state that I would have never explored independently. Without your support this project would not have been possible! Wiley, I especially want to thank you for being our biggest supporter since the project's infancy, and for all the unforeseen assistance you ended up provided my crew, including car towing and GPS recovery. I greatly enjoyed getting to know you, and will always remember your kindness and helpfulness throughout this study!

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Everyone who has conducted ecological research knows the necessity of great field technicians, and I was extremely privileged to have some of the hardest-working, responsible, dependable, conscientious, intelligent, resourceful, and patient field technicians assisting me collect my data. An endless thank you to Rose Agbalog, Jesse Artrip, Lucas Baxley, Jonathan Boerger, Clinton Brooks, Ian Dudley, Talesha Karish, and Kimberly Stocks. The blood, sweat, and tears you each devoted to this project did not go unnoticed, and will always be remembered! A special thanks in particular to Kim who worked both years and collected all the vegetation data independently. Your work ethic will always amaze me! Also, thank you to Brandon Sherrill who assisted in the field both years, and Erin Hamilton who helped enter data.

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Graduate school is meant to be a learning experience and I owe a lot of the knowledge I gained over the past three years to the relationships and interactions I had with other graduate students. I would therefore like to express my deepest gratitude to all the friends and colleagues I had the pleasure of building memories with during my time at NCSU (you know who you are)!

Last but not least, I must thank my mom and dad, to whom I dedicate this thesis. Although, I do not think any parent dreams of their child becoming a wildlife biologist, my parents have always greatly encouraged my interest in this field. Thank you for always supporting me, and for instilling in me the work ethic, organizational skills, and passion for learning that have carried me through to the completion of this research! Also, thank you for

your assistance in the field, and for keeping me, my field techs, and many graduate students satiated with home-cooked meals over these past couple years! I love you both!

TABLE OF CONTENTS

LIST OF TABLES

CHAPTER 2

CHAPTER 3

APPENDIX A

APPENDIX B

APPENDIX C

LIST OF FIGURES

CHAPTER 2

CHAPTER 3

CHAPTER 1

CONCEPTUAL OVERVIEW

Since the industrial revolution scientists have been studying the ever-increasing influence that human civilization has had on nature, culminating in the current age which many deem the "Anthropocene" (Steffen et al. 2011, Caro et al. 2012). A clear component of this influence has been the increase in human-altered landscapes (Vitousek et al. 1997) and destruction of natural habitat (Tilman et al. 1994), fueling what many are considering Earth's sixth major extinction event (Leakey and Lewin 1995, Ceballos et al. 2015). With the advent of this new epoch, some ecologists and biologists have begun to question the fundamental role of conservation biology, which has traditionally focused on the intrinsic value of nature and restoring habitats back to their pre-human-altered states (Soulé 1985). Instead of advocating for the separation of humans and nature, others promote the idea that ecological dynamics and human dynamics are now intertwined (Lui et al. 2007, Kareiva and Marvier 2012) and encourage conservation management to adapt accordingly. The recently proposed concepts of "new conservation science" (Kareiva and Marvier 2012) and "novel ecosystems" (Radeloff et al. 2015) are prominent examples demonstrating the desire for conservation biologists to define, incorporate, and ultimately embrace these dynamic human-altered landscapes into conservation measures for native species. As the most prominent influence of habitat loss and conversion globally, (Tilman et al. 2001, Lambin and Meyfroidt 2011) agricultural lands provide a leading example of human-modified habitats that need to be incorporated into our conservation repertoire in close collaboration with agricultural producers for the future conservation of native species. (Tilman et al. 2001, Lambin and Meyfroidt 2011).

Researchers exploring the conservation benefits of human-modified habitats highlight the flexibility of many species to adapt and exploit these habitats, even those considered habitat specialists (Lugo et al. 2012). Others have underscored how human-modified habitats have become functional replacements of historic landscapes, effectively serving as population sources (Brash 1987, Perfecto and Vandermeer 2015). However, novel landscapes also further complicate ecological research and its ability to identify fundamental relationships occurring in nature (Carpenter 2002). As landscapes become more dynamic and species interactions change and become more complex, relationships for which there is already limited understanding have the potential to become even less understood. Land use change can also lead to the loss of ecological services and precipitate cascading ecological effects causing depauperate biological communities and compromised species persistence (Battin 2004). In addition, due to the fast-paced nature of most human-modifications to natural lands, the need for immediate conservation decisions will only greaten.

This thesis first explores the ecology of an early-successional obligate species, the eastern cottontail (*Sylvilagus floridanus*), within an understudied agricultural system, Christmas tree farms, that dominate the landscape in western North Carolina. We focused on two biological processes germane to valuing Christmas tree farms for conservation of cottontails and other early-successional obligate species, resource selection and survival rates. The former leads to a greater understanding of species-habitat relationships, and the latter to inferences about demographic consequences of human-modified habitats and their management.

Secondly, this thesis addresses the rapidity with which landscape changes are occurring, the need for quick decisions, and the scarcity of data associated with most human-modified habitats. Although the collection of empirical data will forever be the scientific (and preferred) standard (O'Neill et al. 2008), recently there has been a push to consider the utility of expert knowledge in prompting conservation decisions. The impetus to explore this alternative also stems from inadequate funding to conduct needed, full-scale research (O'Hagan 1998, Martin et al. 2005, Kuhnert et al. 2010, Perera et al. 2012). In the context of these realities, we combine recent advances in Bayesian ecological models and expert elicitation techniques to determine if expert knowledge provides a useful benchmark with which to help guide management of human-modified lands (Martin et al. 2005, Kuhnert et al. 2010, Perera et al. 2012). Specifically, we combined empirical data on cottontail habitat use of Christmas tree farms with expert knowledge from three mammalian experts on habitat use by cottontails. Our objective was to determine if expert information (priors) performed better at predicting occurrence of cottontails on managed habitats than a model without prior information (i.e., non-informative prior). Collectively, this thesis expands knowledge about the ecology of cottontails on a human-modified habitat in western North Carolina, demonstrates how to incorporate expert knowledge into ecological models, and evaluates the utility of expert knowledge in predicting ecological relationships and guiding future ecological decisions for data-poor environments.

As this research, which constitutes my thesis, reflects the work of many (see Acknowledgements section), I use the collective "we" throughout the thesis.

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CHAPTER 2

Home Range, Habitat Use, and Survival of Eastern Cottontails (*Sylvilagus floridanus*) on Christmas Tree Farms in Western North Carolina

ABSTRACT

Most human-modified lands affect species persistence, but in some cases, these habitats retain ecological resources to support native wildlife species. We studied eastern cottontails (*Sylvilagus floridanus*) habitat use and survival on Christmas tree farms, an understudied agricultural system in western North Carolina, to assess its potential value for conservation. We radio-tracked 57 cottontails on 5 farms from March 15 to June 30, 2014 and 2015. We characterized habitat, occurring inside and outside farms, for individuals with ≥ 30 telemetry locations calculated 95% fixed kernel home ranges, and analyzed habitat selection using discrete choice analysis. We used known-fates analysis to calculate weekly study-period survival, and extrapolated estimates of breeding season and annual survival rates. Average home range size was 6.23 ha with males averaging 9.17 ha and females 3.39 ha. Cottontails selected habitat in proportion to its availability, with males avoiding fields containing extra-small Christmas trees. The probability of selecting a Christmas tree field increased as the proportion of herbaceous cover increased. Estimated weekly study-period survival was 0.98 ± 0.01, with breeding season survival estimated at 0.55 ± 0.17 (Mar-Sept) and annual survival at 0.35 ± 0.18. These estimates were similar to those reported for other types of agricultural habitats. Based on results from this study, Christmas tree farms provide suitable habitat for eastern cottontails, and possibly for other early successional habitat species in North Carolina.

Their conservation potential could be enhanced if their management is conducted in partnership with stakeholders.

INTRODUCTION

Human activities and population growth have transformed global landscapes into patchworks of habitats of varying resource qualities for native species (Sala et al. 2000, Daily 2001, Radeloff et al. 2015). The physical modification of natural landscapes has led to habitat loss, degradation, fragmentation, isolation, decreased connectivity, and creation of new ecological boundaries (Ewers and Didham 2006, Fischer and Lindenmayer 2007). Under these conditions, species vulnerability may increase as colonization/extinction processes are altered, species interactions and behaviors change, and their ability to adapt to remnant habitat patches unsuccessful (Fischer and Lindenmayer 2007). Because land is becoming a scarce resource at the global scale (Lambin and Meyfroidt 2011), there is a growing need to understand how native species may respond to human-modified landscapes. While previous findings indicate that human-modified habitats can be detrimental to some species (Ewers and Didham 2006, Fischer and Lindenmayer 2007), there is growing evidence that suggests they might sometimes provide similar ecological services to the habitats being replaced (Daily 2001, Lugo et al. 2012, Perfecto and Vandermeer 2015, Radeloff et al. 2015). In such instances, a greater ecological understanding of species use of these habitats could be used to inform management decisions to minimize adverse effects on native fauna (Daily 2001, Hobbs et al. 2006, Radeloff et al. 2015). We define native fauna as species that have historically occurred as part of an ecosystem in a specific location.

Agriculture is a driving force of global habitat alteration (Tilman et al. 2001, 2002, Lambin and Meyfroidt 2011). It is estimated that 10^9 hectares of natural ecosystems will be converted to agriculture by 2050 (Tilman et al. 2001). Agriculture production has been shown to impact wildlife populations both negatively and positively (Mankin and Warner 1977), largely because each agricultural system has its own unique management requirements. In western North Carolina, Christmas tree farms are a dominant agricultural commodity. North Carolina is the second highest producing Christmas tree state in the nation (USDA 2014), generating 7.5 million trees a year (Chastagner and Benson 2000) on approximately 40,352 acres in western North Carolina (USDA 2014). Despite their prevalence, with the exception of Buech (1982), there has been no research aimed at assessing the value (or lack thereof) of Christmas tree farms for wildlife.

The impact of human-modified habitats on wildlife is related to differences between the novel habitat (Christmas tree farms) and the baseline habitat they replace (Radeloff et al. 2015). Although, Christmas tree farms are new to the landscape, their dominant species is the Fraser fir, a tree native to North Carolina. Historically landscapes where the Christmas tree farms occur were dominated not by Fraser fir but by deciduous forests (e.g. oak, chestnut; Dyer 2006). However, the use of native vegetation (Fraser firs) may ameliorate some ecological impacts as this species is known to provide food and shelter to many species in western, North Carolina (NCWAP 2015).

This study was designed to better understand the conservation value of Christmas tree farms using eastern cottontails (*Sylvilagus floridanus*) as the biological models. Eastern cottontails have been a model species to assess wildlife use of agricultural landscapes due to their prevalence and ease of capture (Trent and Rongstad 1974, Allen et al. 1982, Swihart and

Yahner 1982a, 1984, Morgan and Gates 1983, Althoff and Storm 1989, Mankin and Warner 1999a, 1999b, Bond et al. 2001b). As early successional obligates (Litvaitis 1993, Fuller and DeStefano 2003), cottontails traditionally thrive near agricultural landscapes that provide dense shrub land and old-field habitat (Dalke and Sime 1941, Sweetman 1944, 1949, Chapman et al. 1980). However, cottontails are also sensitive to changes in agricultural practices. It is believed that some cottontail populations are declining due the increasing mechanized farming that discourages the occurrence of brush piles, shrubby borders, and hedgerows around fields (Mankin and Warner 1999b, Yarrow 2009, Scharine et al. 2011). Other species of cottontails, such as the New England cottontail (*Sylvilagus transitionalis*), are declining due to lack of early-successional habitat on the landscape in general (Litvaitis 1993).

Our assessment of the potential conservation value of Christmas tree farms focused on factors influencing habitat use and their implication on survival rates for eastern cottontails. Specifically, we estimated: 1) home range size and habitat preferences of eastern cottontails among multiple habitat classes characterizing Christmas tree farms, and 2) weekly study-period survival, extrapolating breeding season and annual survival rates to compare to previous studies conducted on other human-modified landscapes. Because management of Christmas tree farms differ from other agricultural crops, we hypothesized that eastern cottontail home range sizes would be smaller because tree cover and associated understory habitat is available on the landscape longer than monoculture row crops. Christmas tree fields not only provide more cover for cottontails, but they also retain similar early-successional forage through forbs and grasses as other human-modified landscapes. For those reasons, we also expected cottontails to select habitats with the highest combination of Christmas tree and herbaceous cover and exhibit higher survival than on other agricultural landscapes where cottontails have been studied. We discuss the implication of our findings in the context of the ability of Christmas tree farms to provide suitable habitat to native wildlife, and to help guide management of this human-modified habitat to achieve that conservation goal.

METHODS

STUDY SITE

We sampled cottontails on five Christmas tree farms in the Ashe and Alleghany counties of western North Carolina. These included: Omni (OM; Lat. = 36.28^0, Long. = -81.38^0), Mistletoe Meadows (MM; Lat. = 36.41^0, Long. = -81.30^0), Gardner (GD; Lat. = 36.37^0, Long. = -81.25^0), Sturgill (CS; Lat. = 36.48^0, Long. = -81.29^0), and Tucker (DT; Lat. = 36.43^0, Long. = -81.28^0) (Figure 1). Farm sizes were: 48.32 ha (OM), 28.03 ha (MM), 6.83 ha (GD), 39.26 ha (CS), and 14.41 ha (DT), with elevation ranging approximately from 850 to 1,100 MASL. We sampled three of the five farms (OM, GD, and CS) in both 2014 and 2015. MM was only sampled in 2014, and DT was only sampled in 2015, yielding four Christmas tree farms sampled per year.

We selected farms owned by producers willing to participate in our study, implementing integrated pest management (IPM) practices, and bordered by natural hardwood forest. IPM is a proactive management strategy where farmers closely monitor their crops in order to predict potential crop damage before it happens. This usually results in less pesticide and fertilizer application as growers distinguish which species are true crop pests, saving them time and money. IPM also promotes selective ground cover growth since certain understory plants can deter erosion, promote root growth, attract beneficial insects to control Christmas tree pests, and increase wildlife biodiversity (Davis et al. 2009).

We sampled farms dominated by Fraser firs (*Abies fraseri*), a native species that represents over 90% of all Christmas trees produced in North Carolina (NC Christmas Tree Association 2016). The majority of the farms implemented block planting of Christmas trees instead of inter-planting. Block planting is a management practice where an entire “block” (or field) of trees is viewed as the management unit, with each block containing uniform size-classes of trees and management treatments (weed control, fertilization, sheering, etc.) (Heiligmann et al. 2008). In contrast, inter-planting is a management practice where the individual tree is considered the management unit. Immediately after a tree is harvested it is replaced by a seedling, resulting in differing size classes of trees and management needs within a field (Heiligmann et al. 2008). CS and MM were the only farms to incorporate a mixture of both planting techniques in some of their fields. The dominant age class of trees ranged from 5-7 years old. The standard “consumer-preferred” Christmas tree of 1.83- 2.44 meters takes approximately 6-8 years to produce (Heiligmann et al. 2008), with Christmas trees greater than 3.05 meters (≥10 years) being undesirable.

The dominant overstory species was the Fraser fir (*Abies fraseri*) with occasional occurrence of white pines (*Pinus strobus*), blue spruce (*Picea pungens*), Leyland cyprus (*Cupressocyparis leylandii*), concolor fir (*Abies concolor*), and boxwood (*Buxus L. spp.)*. The prominent understory species included white clover (*Trifolium repens*), common chickweed (*Stellaria media*), mouse-ear chickweed (*Cerastium vulgatum*), red clover (*Trifolium pretense*), velvet grass (*Holcus lanatus*), blue violet (*Viola papilionacea*), shamrock (*Oxalis spp*.), goldenrod (*Solidago spp*.), tall fescue (*Schedonorus arundinaceus*), hairy bedstraw (*Galium pilosum*), yarrow (*Achillea millefolium*), buffalo grass (*Anthoxanthus odoratum*), horseweed (*Conyza canadensis*), orchard grass (*Dactylis glomerata*), dandelion (*Taraxacum *officinale*), blackberry (*Rubus spp.*), Carolina horsenettle (*Solanum carolinenese*), common ragweed (*Ambrosia artemisiifolia*), hawksbeard (*Crepis capillaris*), ox-eye daisy (*Chrysanthemum leucanthmum*), nimblewill (*Muhlenbergia schreberi*), Virginia creeper (*Parthenocissus quinquefolia*), birdeye speedwell (*Veronica persica*), Queen Anne's lace (*Daucus carota*), hairy bittercress (*Cardamine hirsute*), Devil's darning needles (*Clematis virginiana*).

Some predator species present in the study area likely included coyote (*Canis lantrans*), red fox (*Vulpes vulpes*), gray fox (*Canis cinereoargenteus*), raccoon (*Procyon lotor*), bobcat (*Felis rufus*), long-tailed weasel (*Mustela frenata*), domestic cat (*Felis catus*), domestic dog (*Canis lupus familiaris*), red-tailed hawk (*Buteo jamaicensis*), common crow (*Corvus brachyrhynchos*), barred owl (*Strix varia*), great horned owl (*Bubo virginianus*), barn owl (*Tyto alba*), black rat snake (*Pantherophis obsoletus*), and timber rattlesnake (*Crotalus horridus*) (Haugen 1942, Fitch 1963, Chapman et al. 1980, Wittenberg 2010). Hunting also occurs on these farms during the North Carolina cottontail hunting season (Nov-Feb).

We designated field boundaries by grouping areas containing trees of similar species, size, and subject to identical management practices. Field designations typically aligned with landowner boundaries, separated by grassy roads approximately 3-5 meters in width. Fields containing Fraser firs were categorized independently both by tree size and harvest class. Tree size included extra small (XS; 0.31-0.61 meters), small (S; 0.62-1.22 meters), medium (M; 1.23-1.83 meters), large (L; 1.84–2.44 meters), extra-large (XL; ≥ 2.45 meters), and mix (varying tree sizes). Any fields left unplanted were labeled "open fields." Hardwood forest was categorized as "hardwood." Edge habitat consisting of grassy roads alongside fields or hardwoods was categorized as "edge." Any fields on farms containing species other than Fraser firs (e.g. boxwoods) were combined with mixed size Christmas tree fields, and habitats selected by cottontails on neighboring properties (excluding hardwoods) under “other/mix.”

We quantified the percentage vegetative cover in each field on every farm by creating 10x10 meter quadrants adopted from the NC Vegetation Survey protocol (Peet et al. 1998). Vegetation data were collected in the form of percent herbaceous cover estimates in 5% increments for each quadrat, performed by the same observer both years to reduce variation in estimates. In brief, one or two 10x10 m quadrats were created in each farm field in a location deemed representative of species composition, once during each sampling season. Representative areas were selected after walking through each field multiple times and visually assessing species composition within the entire field. Two quadrats were established if the vegetation within a field was highly heterogeneous or if the field was larger than most others on the farm in question. We sampled farms OM, GD, and CS both years (2014 & 2015) and averaged their field’s percent herbaceous cover estimates. We calculated the weighted average proportion of herbaceous cover in fields within home ranges (*Herb*) by multiplying the estimate per field by the field’s area in the home range, and then dividing it by the sum of all the fields in the home range. This cover estimate was restricted to analyses looking at habitat preference in Christmas tree fields and open fields only. Herbaceous cover data were not recorded for edge, hardwood, or other/mix habitat occurring outside of the farm boundaries.

CAPTURE AND HANDLING

Forty box traps were used each year to capture eastern cottontails. In 2014, we opportunistically trapped on four farms (OM, GD, CS, and MM), placing eight box traps in five fields spread across each farm. We targeted fields believed to contain the most preferred cover for cottontails to maximize capture probability as prior history of trapping of cottontails on Christmas tree farms in the literature had not been reported. Traps remained open and were checked twice daily until an individual was captured. Five cottontails were radio-collared on each farm. In 2015, we modified our trapping technique to systematically sample all habitats available to rabbits. We placed five traps in eight different fields on each farm (OM, GD, CS, and DT). If ≤ 8 habitat types occurred on a farm, the remaining traps were placed in the most prevalent habitats. Traps were checked twice daily. During the first three trap-days only one rabbit per field was collared. On the third and subsequent days, if collars remained, they were randomly distributed to any rabbits captured in all fields. Ten cottontails were radio-collared on all farms except GD, where only 9 were captured.

We used a mixture of collapsible Tomahawk wire live traps 66 x 23 x 23 cm and 51 x 18 x 18 cm (Tomahawk Live Trap Company, Tomahawk, Wis.), and handmade wooden box traps 64 x 23 x 19 (North Carolina Wildlife Resources Commission) baited with apple and alfalfa cubes to attract and capture cottontails. We covered traps with brush when necessary to shield captured animals from inclement weather. All cottontails were restrained with a cloth sack for processing and were not anesthetized. We sexed and weighed (kg) each rabbit captured. Only adult cottontails (> 0.6 kg) were collared with a VHF radio-collar model MI-2, weighing 27g (Holohill Systems Ltd., Ontario, Canada), that is, less than 5% of their body weight (Wilson et al. 1996). We trapped mid-March through April of 2014 and 2015, with occasional opportunistic collar deployment occurring throughout the study period as collars were obtained from mortalities. All capture and handling procedures were approved by the Institutional Animal Care and Use Committee under IACUC Permit 13-057-O.

TRACKING

We tracked cottontails using R410 VHF receivers (ATS, Insanti, MN) and 3-element Yagi antennas (ATS, Isanti, MN). We determined their location in the field by honing in on each individual. Cottontail locations were georeferenced using a Garmin eTrex 10 GPS (Garmin International, Inc., Olathe, KS) with GPS error not exceeding 3 meters. Any cottontail mortalities recorded ≤ 7 days post-release were censored due to potential capture myopathy. We monitored all rabbits twice daily, Monday-Thursday, during crepuscular hours (6-10 am, 5-9 pm) when cottontails are most active (Anderson 1975, Chapman et al. 1980, Bond et al. 2001b), and once every Friday from the morning to afternoon (6 am-2 pm) to encompass resting locations. The order in which farms were sampled was rotated to reduce the possibility of introducing systematic sampling biases. To minimize serial autocorrelation, there was a span of at least eight hours between tracking sessions (De Solla et al. 1999). We did not sample at night as research suggests cottontail movement does not differ significantly between nocturnal and crepuscular periods (Bond et al. 2001b), and because of visual difficulty honing in on individuals.

STATISTICAL ANALYSIS

Home range

We estimated study-period home range (March-June) for cottontails that had ≥ 30 telemetry locations (Seaman et al. 1999) using the kernel utilization distribution (Anderson 1982, Worton 1989) estimator “kernelUD” from Package “adehabitat” (Calenge 2006) in Program R (version 3.2.3, R Core Team 2015). Home ranges were constructed using the 95% fixed kernel method (Worton 1989) with ad hoc bandwidth selection. 95% selection was chosen as it is the most widely used (Robert et al. 2012) and reduces the bias of exploratory habitat use outside the bounds of normal activity. The ad hoc bandwidth was selected as it reduces the reference bandwidth (href) until the smallest home range with a contiguous polygon is identified, preventing unnecessary fragmentation of home ranges, and decreasing over-smoothing (Berger and Gese 2007, Jacques et al. 2009, Kie et al 2010). We converted 95% fixed kernel home ranges into shapefiles using Package "rgdal" (Bivand et al. 2015) in Program R to be used in ArcGIS (ESRI 2002) for analysis of resource selection.

We assessed the influence of 5 covariates and 1 interaction term on home range size (ha) using regression analysis in Program R. We explored all possible covariate combinations using the "dredge" function in package "MuMIn" (Barton 2016). Covariates included *Sex*, *Year*, *Area* (farm area, ha), *Herb* (weighted average proportion of herbaceous cover in the home range), *Xmas* (proportion of Christmas tree fields in the home range). The interaction term *Xmas***Herb* was included to explore the potential influence of varying levels of food and cover had on home range. Consistent with other studies of cottontails in agricultural settings, we expected that male cottontails would exhibit larger home ranges than females (Trent and Rongstad 1974, Althoff and Storm 1989, Mankin and Warner 1999a, Bond et al. 2001b) and that home range size would not vary by year.

We used Akaike's Information Criterion (AIC) to select the most parsimonious model (Burnham and Anderson 2002). Models were ranked by AIC, and the model with the lowest AIC value had the most support. Models with ΔAIC $\leq$ 2 were considered models with highest support (Burnham and Anderson 2002). We considered an effect (i.e., covariate beta coefficient) to be strongly supported if the 95% confidence intervals did not overlap zero.

Habitat Selection

We estimated study-period habitat selection (March-June) for each cottontail for which we had ≥ 30 locations, restricting selection inference at the 3rd order (Johnson 1980), or within an individual's 95% fixed kernel home range. We used discrete choice analysis (Ben-Akiva and Lerman 1985) to conduct our analyses because it accounts for changes in resource availability over time (Manly et al. 2002, McDonald et al. 2006), and unequal availability of resources for individuals within the study (Arthur et al. 1996, Manly et al. 2002). This flexibility was important in our study because farms were actively managed inducing differences in resource availability among farms and between years. We assumed that individuals gain some benefit from selecting a given choice set (habitat), and that an individual would choose the habitat that maximizes their benefit or satisfaction (Cooper and Millspaugh 1999).

We tested competing models of cottontail resource selection using a Bayesian mixed effects discrete choice framework in Package "rjags" (Plummer 2016) in Program R and JAGS (version 4.2.0, Plummer 2003). Each model incorporated the percentage of a designated choice set available in an individual cottontail's home range (calculated through ArcGIS), as well as an individual's frequency of use of each choice set (determined by telemetry locations), to model relative selection of the choice set over a designated baseline choice. As a result, betas representing the log odds of selecting each habitat choice over the chosen baseline habitat were provided. We also implemented a Bayesian framework so future analyses could incorporate prior information in the form of expert knowledge.

We fit every discrete choice model with Markov Chain Monte Carlo (MCMC) in JAGS using 5 chains of 100,000 iterations prior to discarding 10,000 burn-ins, and thinning by 10 to reduce sample autocorrelation. For each habitat category (other than the baseline) we incorporated random effects of *Indiv* (individual cottontail) and *Farm* (Christmas tree farm individual was located on), and the fixed effect of *Sex*. By incorporating *Indiv* we assumed that each rabbit has its own habitat preferences and that the betas for each habitat category represent the average preferences across individuals. Similarly, for *Farm* we assumed that habitat preferences varied between farms with the betas representing the average preferences across farms. Finally, the incorporation of *Sex* assumed selection preferences varied between genders.

The Bayesian discrete choice mixed effects model is defined as:

$$(Y_{i1}, \dots Y_{im}) \sim Multinomial\ (p_{i1}, \dots p_{im})\ where\ p_{ij} = \frac{W_{ij}\ \exp(n_{ij})}{\sum_{l=1}^{m}\ W_{i1}\ \exp(n_{ij})}$$

Where Yij is the number of observations of cottontail i in habitat j, and Wij is the percent of cottontail i's home range that is of habitat j. The probabilities varied by cottontail through fixed effect of *Sex* and random effects *Indiv* and *Farm* where:

$$n_{ij} = \beta_{1j} + Sex_i\beta_{2j} + \theta_{farm_{ij}} + \varepsilon_{ij}$$

Where $n_{i1} = 0$ for the baseline $\theta_{kj} \sim Normal\ (0, \sigma_f^2)$ is the random effect for farm k and habitat j, and $\varepsilon_{ij} \sim Normal\ (0, \sigma_e^2)$ is the random effect for cottontail i and habitat j. The prior is $\beta_{kj} \sim Normal\ (0, \sigma_k^2)$ and variances have uniform inverse gamma priors.

We ranked models by their fit and complexity using deviance information criterion (DIC) (Spiegelhalter et al. 2002) and used DIC differences Dbar and pD to evaluate model support. We considered models with DIC ≤ 2 of the top model to have equivalent support, and always selected the most complex model within this range for interpretation in order to account for all relevant effects, and to remain consistent across the study. We used the R Package "coda" (Plummer et al. 2006) to inspect chain convergence of our selected models through calculation of the Gelman-Rubin statistic (Gelman and Rubin 1992), and ensured the fixed effects ($beta\_\{kj\}$) in the models received $\hat{R} \leq 1.02$. Results of the best model were converted into odds to ease interpretation.

We assessed resource selection within the home range at two scales. We first examined cottontail habitat selection at a coarse-scale, incorporating all habitats occurring inside and outside of the Christmas tree farm boundaries within the home range. Selection at this scale provided insights on how human-modified habitats were being used relative to neighboring (often natural) habitats on the landscape. For this analysis, we considered 9 habitat choice sets: *extra-small, small, medium, large, extra-large (Christmas trees), open field, edge, hardwood,* and *other/mix,* and compared their use to the baseline habitat "hardwood" because it represented the natural habitat that would occur on the landscape. We calculated proportions of each choice set within each home range using ArcGIS, and tallied the frequency of occurrence of each cottontail, from telemetry locations, in each habitat choice.

The second level of analysis was conducted at a finer-scale, to gain understanding of differences in use within the modified habitat (the Christmas tree farm) itself. The choice set for this analysis consisted of Christmas tree sizes: *extra-small, small, medium, large,* and *extra-large,* and also considered *Herb* (the weighted average proportion of herbaceous cover of fields used by rabbits within their home ranges). *Herb* was incorporated to gain a better understanding of the influence herbaceous cover played in determining selection of a Christmas tree field, since these two covariates were not mutually exclusive, nor correlated. We chose *large* Christmas trees as our baseline for this analysis because it was the most common Christmas tree size occurring across all farms.

Survival

We estimated weekly study-period survival using a known-fate analysis in Program MARK (White and Burnham 1999). We sampled for roughly 15 weeks (March 15 - June 30) in both 2014 and 2015. A total of 65 individuals were included in the analysis. Cottontails that died within the first week were censored due to potential capture myopathy. For the one cottontail that survived both years we only used the encounter history of 2014. Our analysis included 9 individuals for which we did not estimate home range (*HR*) or corresponding covariates (*Herb* & *Xmas*) as we collected ≤ 30 telemetry locations per individual. Covariate values for these individuals were estimated by using the average across all individuals in order to retain the same mean and variance of the dataset (56 individuals; Cooch and White 2006). Given our choice of a known fates analysis we assumed that that cottontails captured were a representative sample of the population, that radio collars did not affect a rabbit's survival probability, that all tagged cottontails exhibited the same survival probability regardless of time of capture; that fates of individual rabbits were independent of one another; and that censoring of individuals was not related to an animal's fate (Pollock et al. 1989).

We used the weekly study-period survival estimate to extrapolate breeding season (March-September) and an annual survival estimates using the delta method to approximate the standard error (Powell 2007). Extrapolated estimates allowed us to compare our results to other eastern cottontail survival estimates reported in the literature for other agricultural systems (e.g., row crops). Extrapolations assumed that the transformation is approximately linear over the expected range of the parameter, and that there is not considerable variation within the data (Cooch and White 2006, Powell 2007).

We evaluated the influence of 6 covariates on survival. These were: *Sex*, *HR* (95% fixed kernel home range), *Area* (farm area, ha), *Herb* (weighted average proportion of herbaceous cover in the home range), *Xmas* (proportion of Christmas tree fields in the home range), and *Year* (2 groups: 2014 and 2015). The latter was included to determine if there were inter-annual differences in survival. We tested sex and home range because exposure to mortality factors (e.g., predators) might be different for male and females due to varying reproductive behavior and related home range sizes. We expected survival to be positively influenced by farm size as larger farms contain a greater extent of *Herb* (food) and *Xmas* (cover) and subsequently expected *Herb* and *Xmas* to have a positive influences on survival as well. Because there was a possibility that survival rates varied as a function of one covariate (e.g., *Herb*) differently at different levels of another covariate (e.g., *Xmas*), we also considered the influence of two interaction terms: *Xmas*Herb* and *Herb*HR*. Lastly, we assessed whether there were seasonal variation within the study period using a linear (T) and quadratic (T^2) terms.

We used Akaike's Information Criterion (AIC) to select the most parsimonious model (Burnham & Anderson, 2002). Models were ranked by AIC, and the model with the lowest AIC value had the most support. Models with ΔAIC ≤ 2 were considered models with highest support (Burnham & Anderson, 2002). We considered an effect (i.e., covariate beta coefficient) to be strongly supported if the 95% confidence intervals did not overlap zero.

RESULTS

HOME RANGE

We captured 138 individuals (135 adults, 3 juveniles) and radio collared 70 individuals (35 males, 35 females). During the study, 5 cottontails died within 7 days of capture and were censored from the survival analyses due to capture myopathy. Fifty-seven cottontails (29 female, 28 male) yielded ≥ 30 locations, and were used to estimate home range and habitat use, resulting in a mean home range size of 6.23 ha (Table 1, Appendix A) (Figure 2). Variation in home range size was best explained by a model that featured *Area*, *Sex*, and the proportion of *Xmas* and *Herb* cover (AICc *wi* = 0.51). The next best supported model (AICc *wi* = 0.16), although it received an ΔAIC > 2, differed only in that it featured the interaction of *Xmas* and *Herb*. We focused on the best supported model (without the interaction) for interpretation of the results (Table 1, Appendix B). We found that as proportion of herbaceous cover (*Herb*) and Christmas tree fields (*Xmas*) in the home range increased, the size of cottontail home ranges decreased (Table 1). Also, on average, male cottontails have study-period home range sizes 5.11 ha larger than females, and for every hectare increase in farm area there is a decrease in average cottontail home range size by 0.13 ha (Table 1).

HABITAT SELECTION

Hardwoods comprised the largest proportion of the average cottontail's home range, followed by large and extra-large Christmas trees (Table 2). Extra-small and small Christmas trees were the least prevalent in the average rabbit's home range. The habitat class with the greatest number of telemetry locations was hardwood forest followed by large and extra-large Christmas trees (Table 2). Within Christmas tree farms, the largest proportion of herbaceous cover occurred within large and extra-large Christmas tree fields. Also, large Christmas trees were the most prevalent tree type across all farms, followed by extra-large and medium Christmas trees.

The discrete choice model with highest support at the coarse-scale (when resources within and outside farms were considered) featured the fixed effect of *Sex* and random effects of *Indiv* (individual) and *Farm* (DIC = 1294; Table 1, Appendix C). Examination of the Gelman-Rubin statistic for fixed effects ($beta\_\{kj\}$) within the full model indicated chain convergence ($\hat{R}$ $\leq$ 1.01). This model indicated that male cottontails were actively underusing (selecting against) extra-small Christmas trees, selecting them 14.3 times less often than hardwoods (Mean = -3.37, CI = -5.93, -0.94). No other term in the model suggested strong resource selection, indicating that cottontails did not disproportionally select other habitats on Christmas tree farms in comparison to surrounding hardwood forest (Table 3). Analysis of random effect standard deviations: *Indiv* (Mean = 2.97) and *Farm* (Mean = 0.50) indicated greater variation between individuals when it comes to habitat selection in and around Christmas tree farms than among farms (Table 3).

The discrete choice model with highest support at the finer-scale (considering resources available within Christmas tree fields) of analysis featured the fixed effect of *Sex* and random effects of *Indiv* (individual) and *Farm* (DIC = 4755; Table 2, Appendix C). Examination of the Gelman-Rubin statistic for fixed effects ($beta\_\{kj\}$) within the full model indicated chain convergence ($\hat{R}$ $\leq$ 1.02). *Herb* had a strong influence on resource selection (Mean = 0.18, CI = 0.02, 0.33). The odds interpretation for *Herb* indicated that everything else being equal between habitat choices, an increase in cover from 0 to 100% would increase selection of a habitat by cottontails by 20% (Table 4). No other term in the model suggested strong resource selection, indicating that cottontails did not disproportionally select any Christmas tree cover category over large Christmas trees. Analysis of random effect standard deviations: *Indiv* (Mean = 9.51) and *Farm* (Mean = 6.31), indicates greater variation between cottontails when it comes to selection of Christmas tree fields than among farms (Table 4).

SURVIVAL

Variation in survival rates was not explained by any of the covariates considered in this study. Eight of the 11 models had roughly equal support (ΔAICc ≤ 2), thus, we model averaged our results (Table 5). We calculated model averaged weekly study period survival at 0.98 (SE = 0.01), and extrapolated breeding season (Mar-Sept) 0.55 (SE = 0.17) and annual survival rates 0.35 (SE = 0.18).

DISCUSSION

We quantified habitat use and weekly study-period survival to assess the conservation value of Christmas tree farms for eastern cottontails in North Carolina. Christmas tree farms are novel habitats prevalent in the western region of the state, a landscape historically dominated by southern Appalachian oak-pine forest (U.S. Forest Service 1997, Dyer 2006). Habitat conversions are typically associated with loss of ecological services (e.g., pollination, viability of gene pools, habitat for biodiversity) and considered detrimental to conservation (Battin 2004, Radeloff et al. 2015). However, in some instances, these habitats may retain the ability to provide adequate resources to achieve conservation objectives for native species (Radeloff et al. 2015). The metrics measured in this study not only provide a quantitative assessment of how resources were used, but a basis to evaluate the demographic implications for cottontails using Christmas tree farms (Battin 2004).

The unique habitat structure of Christmas tree farms provides both shelter and forage resources to cottontails through densely-planted Christmas trees and early-successional forbs and grasses. We found decreasing home range sizes as the proportions of herbaceous cover and Christmas tree fields increased within the home range. This relationship is supported by the fact that cottontails rely heavily on adequate cover (Swihart and Yahner 1982b, Althoff et al. 1997, Mankin and Warner 1999a) and that herbaceous vegetation comprises the majority of the eastern cottontails diet (Dalke and Sime 1941, Chapman et al. 1980). Our results also indicated that home range size decreased as the size of the Christmas tree farm increased. Although, we only sampled 5 farms, the implications of these results present two different ecological, non-mutually exclusive possibilities that should be explored in future studies. First, the spatial arrangement and quantity of resources in larger farms might differ from smaller ones. Second, larger farms could harbor higher densities of cottontails causing concomitant home range size reduction. Previous studies have found positive correlations between eastern cottontail abundance and increased density of groundcover vegetation (Haugen 1942, Althoff et al. 1997, Bond et al. 2002), shrubby vegetation (Swihart and Yahner 1982b, Boyd and Henry 1991, Althoff et al. 1997), and woody vegetation (Allen et al. 1982, Swihart and Yahner 1982b), all prevalent in and/or around Christmas tree farms.

The average cottontail home range in our study was 6.23 ha (males = 9.17 ha; females = 3.39 ha). Sex-specific differences in home range size were consistent with findings reported in the literature (Trent and Rongstad 1974, Althoff and Storm 1989, Mankin and Warner 1999a, Bond et al. 2001b), with males exhibiting larger home ranges than females. We also note that the size of the home ranges in our study were slightly larger than in other studies. For example, Bond et al. (2001b) reported that 95% fixed kernel home range for males was 5.98

ha (SE = 0.57) and 3.04 ha (SE = 0.33) for females during breeding season (Feb-Sept) in a wildlife management area in Mississippi with row crops. Walker (2003) estimated average breeding season (Jan-Sept) 95% adaptive kernel home range size for cottontails on the same wildlife management area studied by Bond et al. (2001b) as 4.21 ha. The similarity of our breeding season home range findings to those presented by both studies are of particular interest as their study area was actively managed to enhance wildlife species presence. The larger home range estimates we report could reflect differences in arrangement and quantity of resources available on Christmas tree farms. However, it is also important to note than we conducted our study early in the breeding season. During this period home ranges are in flux, generally growing in size for both sexes (Trent and Rongstad 1974). Later in the season, female home ranges decrease in size by early summer (mid-May-mid-July), and males with cessation of sexual activity in late summer (mid-July-mid-Sept). Other studies have also reported home ranges comparable to ours, but in contrast, these studies collected data outside of the breeding season. For example, Mankin and Warner (1999a) reported 90% fixed kernel home range estimates as 26.1 ha (males) and 9.3 ha (females) on an Illinois landscape dominated by row crops (June-Oct).

Cottontails did not exhibit strong selection preferences (or avoidances) for resources on and around Christmas tree farms, nor at the finer-scale within farms. Analyses indicated, however, that male cottontails actively selected against extra small Christmas trees relative to hardwood forest and that at the finer-scale, increasing herbaceous cover in any given habitat would increase the probability of it being selected by cottontails. Proportional use of habitats is likely due to their prevalence on the landscape, particularly fields with larger size trees. On the other hand, results also point at the possibility that fields of extra-small trees represent the least suitable habitat for cottontails (e.g. greater exposure to predation). These fields are devoid of tree cover, and provide minimal forage because understory vegetation must be reduced to avoid shading growing saplings. Our results also indicated that a greater amount of selection variation existed among individuals than among farms. Such individual variation might make it difficult to discern selection by cottontails at the 3rd order (Johnson 1980). These results, however, do not preclude the possibility that cottontails exhibit resource selection at other orders (4th order; Johnson 1980) such as selection of particular vegetative species within the herbaceous layer.

Christmas tree farms provided resources used in proportion to their availability, with nearly all tree classes providing some level of both cover and food for all cottontails. Our findings are in accord with expectations that an early-successional obligate species like cottontails should do well on Christmas tree farms as farms undergo regular disturbance through management, enhancing the early-successional herbaceous cover available on these habitats. Decision makers could consider working with Christmas tree producers and wildlife biologists to identify Christmas tree rotations that maximize fields with larger size Christmas trees and more herbaceous cover for the benefit of cottontails. Importantly, unlike other forms of agriculture (e.g. row crops), Christmas tree farms do not undergo the punctuated, intense management that leaves land barren for large portions of the year. For example, cottontail use of row crop croplands (e.g. soybean and corn) is restricted to the growing season, greatly avoiding those areas after harvest (Boyd and Henry 1991, Althoff et al. 1997, Mankin and Warner 1999a, Bond et al. 2002). The difference in the way Christmas tree farms are managed year-round reduces sharp seasonal contrasts in resource availability, likely diminishing negative impacts on native wildlife in comparison to other agricultural regimes.

Our estimates of survival were similar or slightly higher than those reported for other human-modified landscapes. Our breeding season (55 ± 17) and annual survival (35 ± 18) estimates were similar to the 57.2% (breeding season) and 20% (annual survival) reported by Trent and Rongstad (1974) on an experimental row crop farm in Wisconsin. Bond et al. (2001) reported an estimate of annual survival of 20% (SE = 5.22) on a managed wildlife area with row crops in Mississippi, and Hunt et al. (2013) estimated annual survival as 30.4% (SE = 12.9) in a urban park in Chicago. Boland and Litvaitis (2008) reported a range in annual survival of 19% to 40% in a non-hunted area of Cape Cod, Massachusetts. We acknowledge that statements about the suitability of Christmas tree farms would be stronger if our survival estimates were comparable to estimates obtained from non-modified habitats, and if mortality data was collected year-round. These are both very important gaps in our knowledge that should be addressed in future studies.

The importance of quantifying the value of habitats for conservation has gained significance in light of the dominant role human-modified habitats are playing on landscapes worldwide (Radeloff et al. 2015). Such habitats could represent conservation opportunities, particularly if their management is directed towards features that enhance fitness parameters like reproduction and survival. This study not only documented the use of habitats by cottontails on Christmas tree farms in western North Carolina, but additionally quantified weekly study-period survival, a fitness parameter. The use of habitats and survival rates of eastern cottontails reported in this study suggest that Christmas tree farms are not ecological traps (Battin 2004), but instead, have the potential to supporting other early successional obligate species on the landscape. This potential should be assessed more broadly by replicating this study, but focused on other species of interest, and thereby, generate recommendations to guide management and farmers to jointly maximize the opportunity that Christmas tree farms represent for wildlife conservation in North Carolina.

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TABLES AND FIGURES

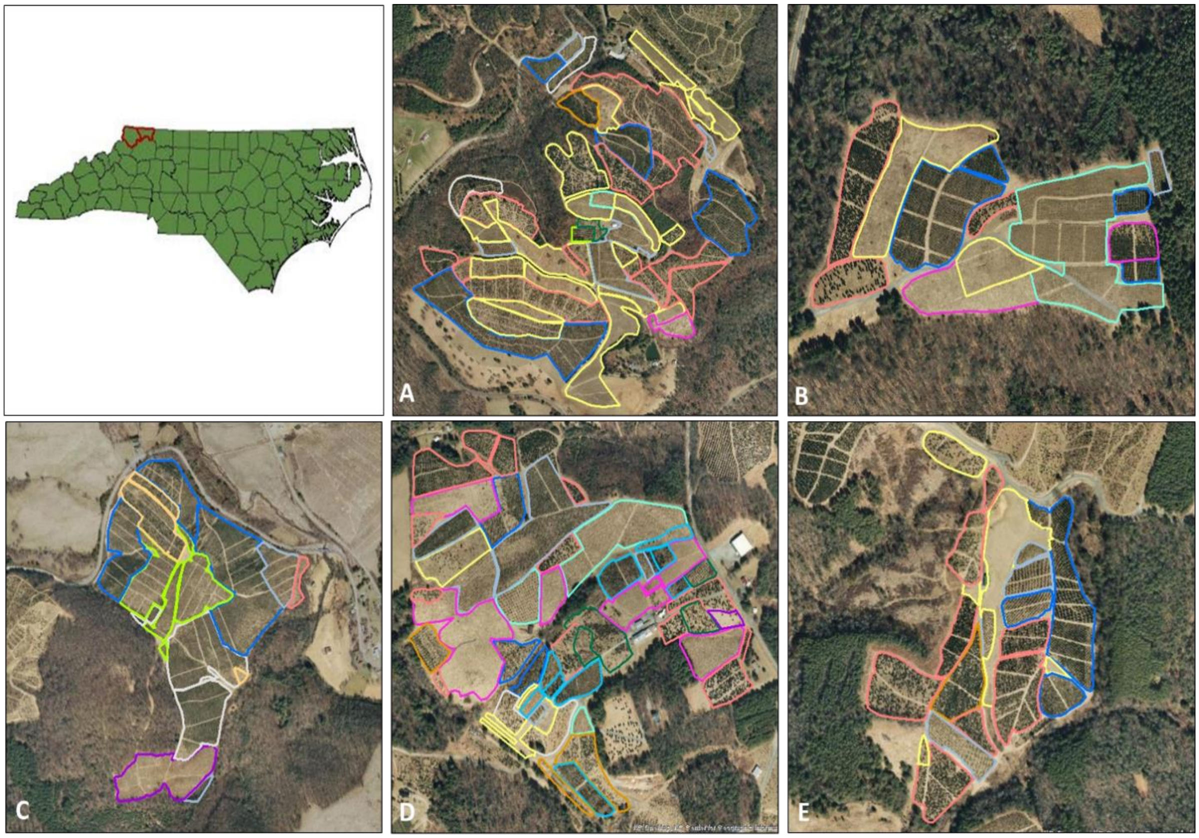

Figure 1. Aerial images of the 2 western North Carolina counties (Alleghany and Ashe), and 5 Christmas tree farms sampled: (A) Omni, Ashe (B) Gardner, Ashe (C) Charles Sturgill, Alleghany (D) Mistletoe Meadows, Alleghany (2014 only) (E) Don Tucker, Alleghany (2015 only).

Table 1. Coefficients from AICc top ranked linear model testing effect of covariates on size of 95% fixed kernel, breeding season home range sizes (ha) of eastern cottontails on Christmas tree farms in western North Carolina. Covariates include: *Sex*, *Area* (farm area, ha), *Xmas* (proportion of Christmas tree fields in a home range), and *Herb* (weighted average proportion of herbaceous cover in the home range).

	Estimate	SE	t value	Pr (>|z|)	
(Intercept)	16.47	2.75	6.00	0.00	***
Sex (Male)	5.11	1.23	4.15	0.00	***
Area	-0.13	0.04	-3.12	0.00	**
Xmas	-7.94	2.55	-3.11	0.00	**
Herb	-10.53	4.25	-2.48	0.02	*

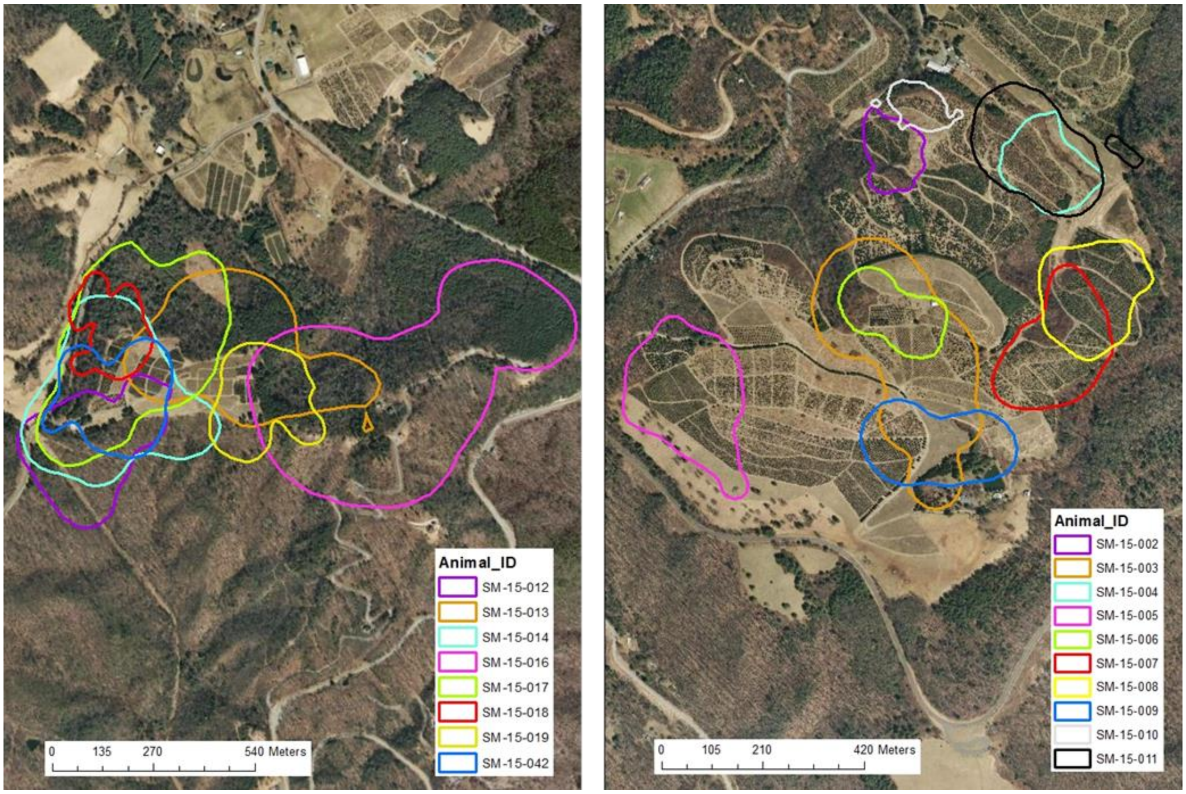

Figure 2. The 95% fixed kernel, breeding season (March-June, 2015) home ranges for 18 eastern cottontails tracked on 2 of the 5 Christmas tree farms sampled in western North Carolina: Gardner farm (left) and Omni farm (right). Home ranges varied from 4.24 ha (SM-15-018) to 32.31 ha (SM-15-016) on Gardner and 1.03 ha (SM-15-010) to 10.54 ha (SM-15-003) on Omni. Gardner was the smallest farm sampled at 6.83 ha, and Omni the largest at 48.32 ha.

Table 2. Summary data for each habitat type found on (and around) the 5 Christmas tree farms sampled in western North Carolina: *Extra-Small, Small, Medium, Large, Extra-Large* (Christmas trees), *Field, Hardwood, Edge*, and *Other/Mix.* Frequency of use (# telemetry locations), average proportion of each habitat type in cottontail home ranges, weighted average proportion of herbaceous cover found in each habitat type, and proportion of each habitat occurring across all Christmas tree farms sampled, is provided.

	Frequency (# of telemetry locations)	Average Proportion in Home Range	Average Proportion Herbaceous Cover	Proportion of Christmas Tree Farms
Extra Small	6	0.01	0.01	0.03
Small	37	0.02	0.03	0.09
Medium	203	0.05	0.06	0.13
Large	957	0.21	0.13	0.48
Extra Large	853	0.16	0.14	0.27
Field	117	0.06	NA	NA
Hardwood	1058	0.32	NA	NA
Edge	257	0.08	NA	NA
Other/Mix	193	0.07	NA	NA

Table 3. Results from Bayesian mixed effects discrete choice model evaluating selection of habitat on (and around) Christmas tree farms in western North Carolina by eastern cottontails in their 95% fixed kernel, breeding season (March-June) home ranges. Model incorporates fixed effect: *Sex* and random effects: *Sigma_Indiv* (variation between individual) and *Sigma_Farm* (variation between farms). Indicator variable of *Hardwoods* was used as a reference to compare other habitat categories: *Extra-Small*, *Small*, *Medium*, *Large*, *Extra-Large* (Christmas tree fields), *Field* (open field), *Edge* (grassy roads between fields), and *Other/Mix* (neighboring habitats occurring off Christmas tree farms/fields on the farms growing plants other than Christmas trees/fields containing mixed Christmas tree sizes). Mean and 95% credible interval (CI) results provided. Odds results provided except for random effects.

		95% CI			95% CI	
	Mean	Lower 2.5%	Upper 97.5%	Mean (Odds)	Lower 2.5% (Odds)	Upper 97.5% (Odds)
Male Extra-Small	-3.37	-5.93	-0.94	0.07	0.00	0.39
Male Small	-1.95	-4.31	0.37	0.29	0.01	1.45
Male Medium	0.22	-1.36	1.77	1.71	0.26	5.90
Male Large	0.53	-0.85	1.93	2.17	0.43	6.89
Male Extra-Large	0.56	-0.84	1.93	2.25	0.43	6.87
Male Field	-1.33	-2.95	0.27	0.37	0.05	1.31
Male Edge	-0.36	-1.61	0.85	0.85	0.20	2.34
Male Other/Mix	-1.54	-3.19	0.11	0.31	0.04	1.11
Female Extra-Small	0.92	-2.56	4.41	12.09	0.08	82.60
Female Small	0.43	-2.85	3.78	6.55	0.06	43.65
Female Medium	-0.10	-2.64	2.47	2.16	0.07	11.85
Female Large	-1.53	-3.32	0.25	0.33	0.04	1.29
Female Extra-Large	-0.18	-2.09	1.74	1.35	0.12	5.71
Female Field	0.37	-1.78	2.49	2.63	0.17	12.05
Female Edge	-0.72	-2.31	0.89	0.68	0.10	2.43
Female Other/Mix	-1.55	-3.76	0.66	0.40	0.02	1.93
Sigma_Indiv	2.97	2.65	3.32	NA	NA	NA
Sigma_Farm	0.49	0.20	1.03	NA	NA	NA

Table 4. Results from Bayesian mixed effects discrete choice model evaluating selection of Christmas tree size and herbaceous cover on Christmas tree farms in western North Carolina by eastern cottontails in their 95% fixed kernel, breeding season (March-June) home ranges. Model incorporates fixed effect: *Sex* and random effects: *Sigma_Indiv* (variation between individual) and *Sigma_Farm* (variation between farms). Indicator variable of *Large* Christmas trees was used as a reference to compare to other Christmas tree size categories: *Extra-Small*, *Small*, *Medium*, and *Extra-Large*. Covariate *Herb* (weighted average herbaceous cover in the home range) was also run in the model. Mean and 95% credible interval (CI) results provided. Odds results provided except for random effects.

		95% CI			95% CI	
	Mean	Lower 2.5%	Upper 97.5%	Mean (Odds)	Lower 2.5% (Odds)	Upper 97.5% (Odds)
Herb	0.18	0.02	0.33	1.20	1.02	1.40
Male Small	-1.58	-6.99	4.03	12.12	0.00	56.16
Male Medium	-0.95	-5.82	4.07	10.98	0.00	58.76
Male Extra-Small	-1.90	-7.35	3.73	15.11	0.00	41.85
Male Extra-Large	-0.14	-4.67	4.73	18.57	0.01	113.41
Female Small	0.42	-5.37	6.17	99.90	0.00	479.09
Female Medium	0.59	-4.89	6.03	103.50	0.01	414.26
Female Extra-Small	0.47	-5.10	6.02	88.99	0.01	413.31
Female Extra-Large	1.06	-3.38	5.57	41.56	0.03	263.06
Sigma_Indiv	9.51	7.09	12.75	NA	NA	NA
Sigma_Farm	6.31	0.73	12.64	NA	NA	NA

Table 5. Known-fate models in Program MARK of 65 collared eastern cottontails tracked March-June, on Christmas tree farms in western North Carolina. Models were ranked by Akaike's Information Criterion and adjusted for small sample size (AICc). Covariates included: *Sex*, *HR* (95% fixed kernel home range), *Area* (farm area, ha), *Year*, *Xmas* (proportion of Christmas tree fields in the home range), and *Herb* (weighted average proportion of herbaceous cover in the home range). Interactions *Herb*HR* and *Xmas*Herb* were also included. We also incorporated a null model, S(.), that represented constant survival, as well as a *T* (liner time trend), and *T^2* (quadratic time trend). *K* indicates the number of estimated parameters.

Model	K	AICc	Δ AICc	AICc wi	Model Likelihood	Deviance
{S(.)}	1	155.05	0.00	0.17	1.00	153.05
{S(Year)}	2	155.52	0.47	0.14	0.79	151.51
{S(Herb)}	2	155.76	0.70	0.12	0.70	151.74
{S(Sex)}	2	155.90	0.85	0.11	0.65	151.88
{S(Area)}	2	156.10	1.05	0.10	0.59	152.09
{S(HR)}	2	156.20	1.55	0.10	0.56	152.19
{S(T)}	2	156.90	1.84	0.07	0.40	152.88
{S(T^2)}	2	156.98	1.93	0.07	0.38	152.97
{S(Xmas)}	2	157.06	2.00	0.06	0.37	153.04
{S(Herb*HR)}	4	158.56	3.50	0.03	0.17	150.50
{S(Xmas*Herb)}	4	159.59	4.54	0.02	0.10	151.53

CHAPTER 3

Utility of Expert Knowledge in Guiding Management Decisions for Wildlife on Human-modified Landscapes

ABSTRACT

Impacts of human-modified landscapes on wildlife remain understudied. Thus, many management decisions are uninformed and made quickly due to limited resources to collect empirical data. Expert knowledge has the potential to inform management decisions. We assessed the utility of expert knowledge for the aforementioned purpose by comparing expert prior predictions of cottontail occurrence in habitat fields on Christmas tree farms to uninformed priors, both coupled with empirical data. We radio-tracked 57 eastern cottontails on 5 farms March-June, 2014 and 2015, and analyzed their habitat selection using a Bayesian mixed effects discrete choice model. We elicited information from 3 regional experts and converted their knowledge into priors. We examined parameter estimates and predictions obtained from Bayesian analyses incorporating informative (expert) priors versus uninformative priors. Posteriors incorporating expert priors were more variable than those using uninformative priors, possibly reflecting the expert's unfamiliarity with the system. Mean squared errors from cross validations (e.g., Christmas tree model: 46.09 [Uninformed] vs. 50.21 [informed]) indicated that expert knowledge did not improve predictions. Expert knowledge was of limited value to inform decisions on cottontail management, but this inference should not be extended to the rest of the early-successional community on Christmas tree farms. Decision makers could opt to collect empirical data in ecological settings under which expert uncertainty is shown to be highest. If expert knowledge is used, we stress the

importance of collecting data using a standardized elicitation protocol that minimizes expert subjectivity, followed by quantitative assessments as the one described in this study.

INTRODUCTION

Unlike other scientific fields, whose research provides clear definitions of what is known and unknown, ecology is based on the premise that fundamental relationships exist within nature that are important to understand, but have yet to be identified (Carpenter 2002). Ecology is notoriously hard to study due to its complex and dynamic nature (Carpenter 2002, Kuhnert et al. 2010). As true experiments are difficult to implement, ecosystem dynamics are typically best understood retrospectively (Carpenter 2002). Because some questions need to be answered before ecological relationships are completely understood, prediction is considered a universal feature of ecological research (Carpenter 2002). This scientific endeavor has become more complicated with increasing human demands on the environment, which are changing ecosystems in unforeseen ways with unpredicted consequences (Vitousek et al. 1997, Carpenter 2002). Most ecologists, therefore, are required to base current management decisions on future predictions of ecosystem states and ecological relationships for which there is currently limited understanding (Carpenter 2002, Kuhnert et al. 2010).

In recent years, the application of expert knowledge to management decisions has gained traction in the field of ecology (O'Hagan 1998, Martin et al. 2005, Kuhnert et al. 2010). This is because most conservation decisions must be made quickly, and collection of empirical data is constrained by limited resources (Sutherland et al. 2004). The reality is that many decisions are often based on informal advice that is undocumented, impossible to trace or test, and that fail to incorporate levels of uncertainty (Sutherland et al. 2004). However, advances in Bayesian ecological models have provided a suitable framework to incorporate expert knowledge, a process that involves the elicitation of information from experts and incorporating it as ‘priors’ or probability distributions. This approach purportedly is better suited to inform predictions and management decisions due to the scale, inherent uncertainty, complexity, lack of data, and urgency associated with most ecological decisions (Kuhnert et al. 2010).

Many researchers have begun to recognize the aforementioned potential, especially in cases where empirical data is limited (Martin et al. 2005, Kuhnert et al. 2010, Drew et al. 2013). Implementing expert knowledge in a rigorous manner could provide a method to combat these uncertainties. Adoption of formal elicitation methods would provide ecologists with a rigorous, repeatable, and measureable framework by which to incorporate non-empirical information (Perera et al. 2012). It can also provide ecologists and wildlife managers a standardized way to identify ecological information gaps, develop future research hypotheses, and estimate and compare the impacts management decisions can have on wildlife species. Expert elicitation can also promote effective collaboration between private landowners and state/federal agencies, enhancing communication and providing a foundation to set shared conservation objectives.

In this study, our objective was to assess the utility of expert knowledge to help inform management decisions in a human-modified habitat, Christmas tree farms in western North Carolina. This ecological setting is characterized by scarce information on how native species respond to management actions. The high degree of uncertainty, lack of empirical data, and prominence of farms on the landscape, make Christmas tree farms a prime example of a system requiring expert knowledge to help guide management, and thus, provide an opportunity to evaluate the utility of expert knowledge. We addressed our objective by first interviewing experts to elicit their knowledge on occurrence and habitat use by eastern cottontails (*Sylvilagus floridanus*) on Christmas tree farms, and converting their knowledge into priors for use in Bayesian models. Second, we collected empirical data on the ecology of eastern cottontails. Finally, we used a Bayesian multinomial discrete choice framework to evaluate the utility of expert knowledge by comparing parameter estimates and predictions resulting from Bayesian analyses with informative (expert) priors versus uninformative priors. Expert elicitation sessions were conducted at the beginning of the study by an independent, experienced elicitator (C. A. Drew, KDV Decision Analysis, Durham, NC), and data (expert priors) were then shared with us to conduct the evaluation. We discuss the implications of expert knowledge in the context of management and conservation in human-modified habitats, and potential applications to other species and ecological settings.

METHODS

STUDY AREA

We sampled cottontails on five Christmas tree farms in the Ashe and Alleghany counties of western North Carolina. These included: Omni (OM; Lat. = 36.28^0, Long. = -81.38^0), Mistletoe Meadows (MM; Lat. = 36.41^0, Long. = -81.30^0), Gardner (GD; Lat. = 36.37^0, Long. = -81.25^0), Sturgill (CS; Lat. = 36.48^0, Long. = -81.29^0), and Tucker (DT; Lat. = 36.43^0, Long. = -81.28^0) (Figure 1). Farm sizes were: 48.32 ha (OM), 28.03 ha (MM), 6.83 ha (GD), 39.26 ha (CS), and 14.41 ha (DT), with elevation ranging approximately from 850 to 1,100 MASL. We sampled three of the five farms (OM, GD, and CS) in both 2014 and 2015. MM was only sampled in 2014, and DT was only sampled in 2015, yielding four Christmas tree farms sampled per year. We selected farms owned by producers willing to participate in our study, implementing integrated pest management (IPM) practices, and bordered by natural hardwood forest. We sampled farms dominated by Fraser firs (*Abies fraseri*), a native species that represented over 90% of all Christmas trees produced in North Carolina (NC Christmas Tree Association 2016). A more detailed description of the vegetative and management components of the study area can be found in chapter 2.

We designated field boundaries by grouping areas containing trees of similar species, size, and subject to identical management practices. Field designations typically aligned with landowner boundaries, separated by grassy roads approximately 3-5 meters in width. Fields containing Fraser firs were categorized independently both by tree size and harvest class. Tree size included extra small (XS; 0.31-0.61 meters), small (S; 0.62-1.22 meters), medium (M; 1.23-1.83 meters), large (L; 1.84-2.44 meters), extra-large (XL; ≥ 2.45 meters), and mix (varying tree sizes). Any fields left unplanted were labeled "open fields." Hardwood forest was categorized as "hardwood." Edge habitat consisting of grassy roads alongside fields or hardwoods was categorized as "edge." Any fields on farms containing species other than Fraser firs (e.g. boxwoods) were combined with mixed size Christmas tree fields, and habitats selected by cottontails on neighboring properties (excluding hardwoods) under "other/mix."

We quantified the percentage vegetative cover in each field on every farm by creating 10x10 meter quadrants adopted from the NC Vegetation Survey protocol (Peet et al. 1998). Vegetation data were collected in the form of percent herbaceous cover estimates in 5% increments for each quadrat, performed by the same observer both years to reduce variation in estimates. In brief, one or two 10x10 m quadrats were created in each farm field in a location deemed representative of species composition, once during each sampling season. Representative areas were selected after walking through each field multiple times and visually assessing species composition within the entire field. Two quadrats were established if the vegetation within a field was highly heterogeneous or if the field was larger than most others on the farm in question. We sampled farms OM, GD, and CS both years (2014 & 2015) and averaged their field's percent herbaceous cover estimates. We calculated the weighted average proportion of herbaceous cover in fields within home ranges (*Herb*) by multiplying the estimate per field by the field's area in the home range, and then dividing it by the sum of all the fields in the home range. This cover estimate was restricted to analyses looking at habitat preference in Christmas tree fields and open fields only. Herbaceous cover data were not recorded for edge, hardwood, or other/mix habitat occurring outside of the farm boundaries.

CAPTURE AND HANDLING

We used a mixture of collapsible Tomahawk wire live traps 66 x 23 x 23 cm and 51 x 18 x 18 cm (Tomahawk Live Trap Company, Tomahawk, Wis.), and handmade wooden box traps 64 x 23 x 19 (North Carolina Wildlife Resources Commission) baited with apple and alfalfa cubes to attract and capture cottontails. We covered traps with brush when necessary to shield captured animals from inclement weather. Forty box traps were used each year, with 5 cottontails being collared on each farm in 2014, and 9-10 in 2015. In 2014, we opportunistically trapped on four farms (OM, GD, CS, and MM), placing eight box traps in five fields spread across each farm. We targeted fields believed to contain the most preferred cover for cottontails to maximize capture probability as prior history of trapping of cottontails on Christmas tree farms in the literature had not been reported. Traps remained open and were checked twice daily until an individual was captured. Five cottontails were radio-collared on each farm. In 2015, we modified our trapping technique to systematically sample all habitats available to rabbits. We placed five traps in eight different fields on each farm (OM, GD, CS, and DT). If

≤ 8 habitat types occurred on a farm, the remaining traps were placed in the most prevalent habitats. Traps were checked twice daily. During the first three trap-days only one rabbit per field was collared. On the third and subsequent days, if collars remained, they were randomly distributed to any rabbits captured in all fields. Ten cottontails were radio-collared on all farms except GD, where only 9 were captured.

All cottontails were restrained with a cloth sack for processing and were not anesthetized. We sexed and weighed (kg) each rabbit captured. Only adult cottontails (> 0.6 kg) were collared with a VHF radio-collar model MI-2, weighing 27g (Holohill Systems Ltd., Ontario, Canada), that is, less than 5% of their body weight (Wilson et al. 1996). We trapped mid-March through April of 2014 and 2015, with occasional opportunistic collar deployment occurring throughout the study period as collars were obtained from mortalities. All capture and handling procedures were approved by the Institutional Animal Care and Use Committee under IACUC Permit 13-057-O. A more detailed description of trapping and processing methods provided in chapter 2.

TRACKING

We tracked cottontails using R410 VHF receivers (ATS, Insanti, MN) and 3-element Yagi antennas (ATS, Isanti, MN). We determined their location in the field by honing in on each individual. Cottontail locations were georeferenced using a Garmin eTrex 10 GPS (Garmin International, Inc., Olathe, KS) with GPS error not exceeding 3 meters. We monitored all rabbits twice daily, Monday-Thursday, during crepuscular hours (6-10 am, 5-9 pm) when cottontails are most active (Anderson 1975, Chapman et al. 1980, Bond et al. 2001b), and once every Friday from the morning to afternoon (6 am-2 pm) to encompass resting locations. The order in which farms were sampled was rotated to reduce the possibility of introducing systematic sampling biases. To minimize serial autocorrelation, there was a span of at least eight hours between tracking sessions (De Solla et al. 1999). We did not sample at night as research suggests cottontail movement does not differ significantly between nocturnal and crepuscular periods (Bond et al. 2001b), and because of visual difficulty honing in on individuals.

EXPERT KNOWLEDGE ELICITATION

Three professional mammologists with extensive regional knowledge in small mammal ecology served as experts for our elicitation procedure. We asked experts to draw upon their direct observational knowledge (e.g., I have observed this species under these conditions), indirect hearsay knowledge (e.g., I am aware of documented cases of this species under this species), and inferential knowledge (e.g., given what I know of this and similar species' behavior and ecology, I would expect it to occur under these conditions). In all cases, the questions prompted experts to provide their expectations regarding occurrence, not judge the quality of the habitat in terms of reproductive success, long-term survival, or other ecological criteria. Our focus was on whether the animals would use the habitat as part of a larger home range territory. During elicitation, experts typically associated increased (or decreased) probability of occurrence with mental models of increased (versus decreased) frequency and/or duration of presence under various habitat conditions.

To elicit expert knowledge of and expectations regarding eastern cottontail occurrence in habitats on Christmas tree farms, we used a questionnaire-based simple direct elicitation technique (Martin et al. 2005, O'Leary et al. 2008). The technique is considered "simple" as it does not require experts to understand statistical probabilities or distributions. It is described as "direct" because it asks experts to predict the sign of coefficients in the model (O'Leary et al. 2008), rather than indirectly derive coefficient estimates from elicited probabilities of occurrence under various habitat scenarios. This method is considered most appropriate for situations where expert knowledge is too limited or uncertain for experts to estimate probabilities (e.g., they expect there will be more, less, or similar occurrence, but cannot estimate these differences quantitatively).

The questions are posed as contrasts (categorical variables) or gradients (continuous variables) and experts responded by providing two pieces of information: (1) an expected response (increase, decrease, or no difference) and (2) a rating of their confidence in that expectation (probability of being right as a numeric score). Specifically, our experts responded to three ecological questions that corresponded to our empirical data of eastern cottontail use of habitats on and around farms. These questions were:

1) How would cottontail occurrence in Christmas tree fields and Open fields compare to occurrence in hardwood forest?
2) How would cottontail occurrence in Christmas tree fields with tree sizes XS, S, M, and XL compare to occurrence in L Christmas tree fields?
3) How would cottontail occurrence respond to increasing percentage of herbaceous cover in a Christmas tree field?

Based on experts' responses to these questions, we calculated estimated prior values for beta coefficients for use in a logistic regression equation of the form:

$$logit(p_i) = \beta_0 + \beta_1 x_{habitat} + \beta_2 x_{size} + \beta_3 x_{cover}$$

We provide a detailed account and example to illustrate how elicited knowledge is converted to prior estimates of beta coefficients in Appendices D and E.

HABITAT SELECTION

We estimated study-period habitat selection (March-June) for individuals that had ≥ 30 locations, restricting selection inference at the 3rd order (Johnson 1980), or within an individual's 95% fixed kernel home range (Chapter 2). We used discrete choice analysis (Ben-Akiva and Lerman 1985) to conduct our analyses because it accounts for changes in resource availability over time (Manly et al. 2002, McDonald et al. 2006), and unequal availability of resources for individuals within the study (Arthur et al. 1996, Manly et al. 2002). This flexibility was important in our study because farms were actively managed inducing differences in resource availability among farms and between years. We assumed that individuals gain some benefit from selecting a given choice set (habitat), and that an individual would choose the habitat that maximizes their benefit or satisfaction (Cooper and Millspaugh 1999). We also assumed that all the cottontails sampled on Christmas tree farms exhibit the same resource preferences.

We tested competing models of cottontail resource selection using a Bayesian mixed effects discrete choice framework in Package "rjags" (Plummer 2016) in Program R and JAGS (version 4.2.0, Plummer 2003). Each model incorporated the proportion of a designated choice set available in an individual cottontail's home range (calculated through ArcGIS), as well as an individual's frequency of use of each choice set (determined by telemetry locations), to model relative selection of the choice set over a designated baseline choice. We implemented a Bayesian framework so future analyses could incorporate prior information in the form of expert knowledge as it is the case presented in this work.

We fit every discrete choice model with Markov Chain Monte Carlo (MCMC) in JAGS using 5 chains of 200,000 iterations prior to discarding 20,000 burn-ins, and thinning by 20 to reduce sample autocorrelation. We incorporated random effects of *Indiv* (individual cottontail) and *Farm* (Christmas tree farm individual was located on) into all discrete choice models predicting resource use by eastern cottontails. We used the R Package "coda" (Plummer et al. 2006) to inspect chain convergence of our selected models through calculation of the Gelman-Rubin statistic (Gelman and Rubin 1992), and ensured betas in the models received $\hat{R} \leq 1.02$. Results of the best model were converted into odds to ease interpretation.

UTILITY OF EXPERT KNOWLEDGE

We fit two different discrete choice models corresponding to the questions asked to our experts. The first model or "habitat model" compared use of Christmas tree fields and open fields to hardwood forest. We chose hardwoods as the baseline habitat as it represents the natural habitat that would occur on the landscape if Christmas tree farms were not present. The second model or "Christmas tree model" compared use of *extra-small*, *small*, *medium*, and *extra-large* Christmas trees to *large* Christmas trees and also incorporated the *Herb* covariate to gain a better understanding of how presence of herbaceous understory cover affects selection. We chose *large* Christmas trees as the baseline habitat as it was the most common Christmas tree size occurring across all farms. We ran each discrete choice model twice: once with the uninformative prior (Mean = 0, Variance = 10) and another time with the informative prior (expert-opinion generated) in order to compare differences in estimates when expert knowledge was and was not incorporated into the models. Informative prior distributions were created from data (mean, standard deviation, and 95% CI) gleaned from the elicitation for each beta.

To further assess the utility of expert opinion, we performed a five-fold cross validation (Boyce et al. 2002) on all models. The five-fold cross validation worked by splitting the data for each discrete choice model into 5 groups, and removing 1 group of data each time it ran. After each run it would use the results of the model (with the 1 group missing) to predict what the group would have actually selected for. Afterwards, it would compare the model predictions to the observed predictions to gain an understanding of the accuracy of model predictions. This would occur 5 times for each model, to test for all 5 groups, and an overall mean squared error would be produced. The version of the model with the lowest mean squared error was considered the more accurate model.

RESULTS

Elicitation results from 3 experts were combined to obtain a mean estimate for all betas (habitat types) utilized in our discrete choice models. For the habitat model, experts indicated that cottontail occurrence would respond positively and strongly to Christmas tree and open fields relative to hardwood forest (Figure 1). The beta mean estimates from the informative posteriors were much larger (95% CIs did not overlap zero) in comparison to the posteriors derived from the non-informative priors (Table 1).

For the Christmas Trees model, experts exhibited varying responses to the predicted occurrence of eastern cottontails within these habitat types (Figure 2, panels A-E). Experts believed that cottontail occurrence would respond positively to *Herb* (A) but were not confident in how much it would be impacted as the spread of the function is very wide across the positive part of the x axis. Experts also indicated that cottontail occurrence would respond positively and strongly to *extra-small* (B), and *small* (C) Christmas trees in comparison to *large* trees. This means experts expected eastern cottontail occurrence to be greater as herbaceous cover increased, and within fields containing smaller Christmas tree sizes. In contrast, experts indicated that cottontail occurrence would respond neutrally to *medium* (D) trees and negatively to *extra-large* (E) Christmas trees with both predictions being weak as their estimates greatly overlapped 0. In these two cases, experts were less confident in their predictions, but implied a neutral to slightly negative impact on eastern cottontail occurrence. Posteriors beta mean estimates derived from the informative priors were much larger for *extra-small*, and *small* (95% CIs did not overlap zero) in comparison to the posteriors derived from the uninformative priors (Table 2). Posterior beta mean estimates derived from the informative priors for *herb*, *medium*, and *extra-large* trees showed relatively similar distributions to the posteriors derived from the uninformative priors.

Five-fold cross validation conducted with the uninformative and informative prior estimates for each beta indicated that uninformative priors had smaller mean square errors, with the habitat model having smaller MSE (46.09) than the Christmas trees model (90.98) (Table3). These results indicated that both models with uninformative priors fit better the empirical data than models incorporating informative (expert) priors.

DISCUSSION

We assessed the utility of expert knowledge as a source of information to help guide management of Christmas tree farms in western North Carolina. Our results showed that experts made a range of predictions on the occurrence of eastern cottontails based on the structure (i.e., tree size) and ground cover in farms. At the course scale (habitat model), experts expected eastern cottontail occurrence would increase in Christmas tree fields and open fields in comparison to hardwood forest. At the fine scale (Christmas tree model), experts expected occurrence of cottontails would increase with decreasing tree size and increased herbaceous cover in farm fields. In our results, updating models with informative priors (expert knowledge) did not improve predictions of cottontail occurrence on either scale of analysis as compared to ignoring expert knowledge and using uninformative priors.

The poor predictive ability of experts is unsurprising given the system is data-poor, and thus, ecological relationships poorly known. In this context, experts relied on general knowledge (inference based on other similar habitats and/or species) and opportunistic observations to make predictions. For example, cottontails are known as early successional obligates, and therefore, attracted to open and disturbed areas where early-successional grasses and forbs are present. These resources are traditionally found in habitats without much over story cover. Therefore, it could have been beneficial to have incorporated experts with more empirical research experience with species similar to the one we tested. It is also possible that experts envisioned higher occurrence in the most open habitats because that is where cottontails are move visible. An alternative explanation is that the farms sampled (N=5) were not representative of all Christmas tree farms on the landscape, possibly obscuring underlying cottontail habitat choices and our ability to assess the benefit of expert knowledge. This is plausible for the “habitat model” where the direction of responses (posteriors) derived from experts + data and uninformative prior + data were positive for Christmas trees, but with varying, low precision levels. In contrast, responses exhibited opposing directions (sign) in several categories for open fields (habitat model) and smaller vs larger trees (Christmas tree model). These opposing responses raised the possibility that lack of knowledge, not poor quality of empirical data, contributed to low utility of expert knowledge.

Skeptics view expert knowledge as undeveloped, fragmented, biased, and uninformative. They argue elicited information can be expressed in different forms (e.g. implicit, qualitative, equivocal) and can be highly subjective if its methods of formulation are not explicit and repeatable (Kynn 2008). We acknowledge that it is possible that expert's predictions about occurrence cannot be equated to expressions of habitat selection, the basis of the empirical data used to test the utility of expert knowledge. This is an important point because habitat selection purportedly confers a fitness value to individuals, requiring experts to condition their predictions on habitat availability and a reference habitat type. Cognizant of this potential shortcoming, we adopted a elicitation approach that focused on stating the expected sign of coefficients rather than directly estimating coefficients (O'Leary et al. 2008), and we framed questions such that responses were conditioned on: 1) a reference habitat, and 2) its value as food and shelter habitat for cottontails, habitat quality attributes with direct implications on survival and reproduction.

If best practices for eastern cottontail management on Christmas tree farms were determined by expert judgement for Christmas tree size and cover, the management decisions would have overvalued the habitats eastern cottontails were using least, and undervalued the habitats they were using most. Our findings also highlight a lost opportunity for expert knowledge to guide conservation of other related species, such as the understudied Appalachian cottontail (*Sylvilagus obscurus*), that occurs on the same landscape as Christmas tree farms in western North Carolina, provided Appalachian cottontails use habitat in a similar fashion. In cases like these, where both data and expert knowledge are extremely limited but the impact on the persistence of an at-risk species is high, it would seem advantageous to restrict expert knowledge to guiding research efforts to reduce key uncertainties, enabling conservation efforts to be initiated with a stronger foundation. We caution readers that the limited utility of expert knowledge in Christmas tree farms should not be generalized to other systems. There are many studies that have been enhanced through the incorporation of expert knowledge (Yamada et al. 2003, Martin et al. 2005, McCarthy and Masters 2005, O'Leary et al. 2008, Murray et al. 2009); especially those for which more general ecological knowledge is available. Importantly, we stress that our work focused on a single species, eastern cottontails, and that extrapolating our species-specific results to the rest of the community is inappropriate. It is possible that the same experts are better at predicting occurrence of other species, and thus, useful in guiding management.

The conservation relevance of this project is underscored by the fact that human-modified habitats, such as Christmas tree plantations, continue to arise across landscapes (Hobbs et al. 2014). This trend has been the impetus for a growing need to use expert knowledge where there is little empirical data. Our work suggested that the utility of expert opinion in such ecological settings could be undermined. While structural uncertainty can be incorporated into an adaptive management framework and addressed through the process of monitoring system responses and model updates (Fackler and Pacifici 2014), it is arguable that collecting empirical data initially to reduce key uncertainties continues to be an alternative to expert knowledge. Our work suggests that decision makers should evaluate carefully whether to use expert knowledge to inform conservation or management decisions. One option in making that determination is to assess the conditions under which expert uncertainty is highest, and thus, of lowest value (Drescher et al. 2008). If elicitation of expert knowledge is adopted, we stress the importance of collecting expert knowledge data using a standardized elicitation protocol that minimizes expert subjectivity, followed by quantitative assessments as the one described in this study.

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TABLES AND FIGURES

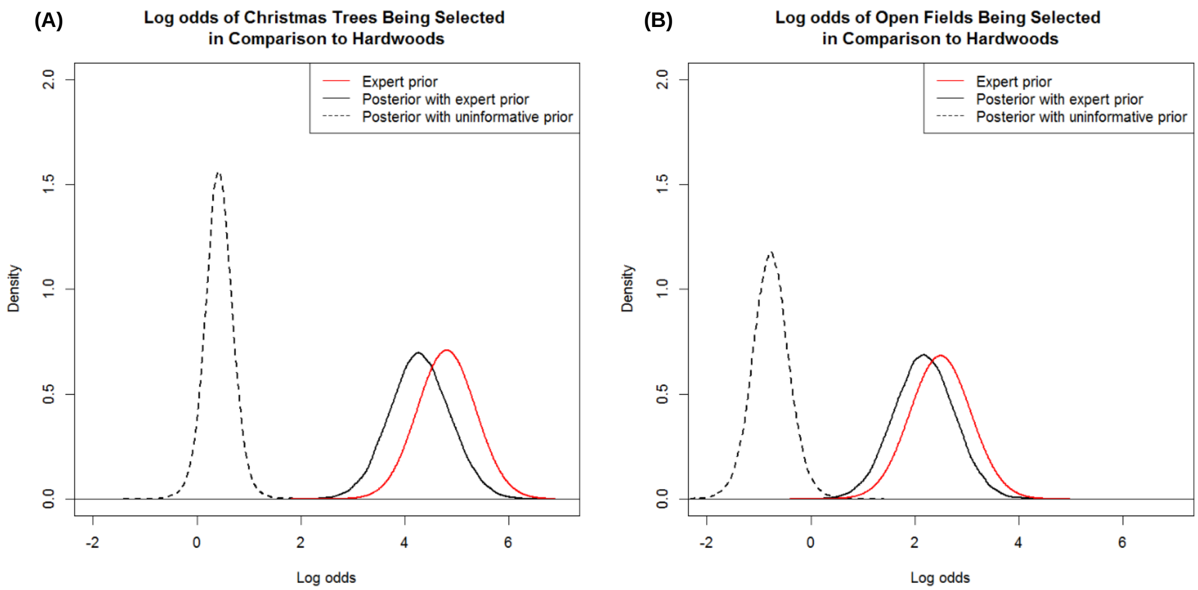

Figure 1. Prior and posterior density functions for a Bayesian mixed effects discrete choice model evaluating eastern cottontail selection on Christmas tree farms within their 95% fixed kernel home ranges. Model is comparing use of *Christmas tree fields (A)* and *Open fields (B)* on farms to surrounding *Hardwoods*. Expert elicited priors are shown (red) along with posterior distributions for the model incorporating both the uninformative prior (dashed) and expert prior (solid).

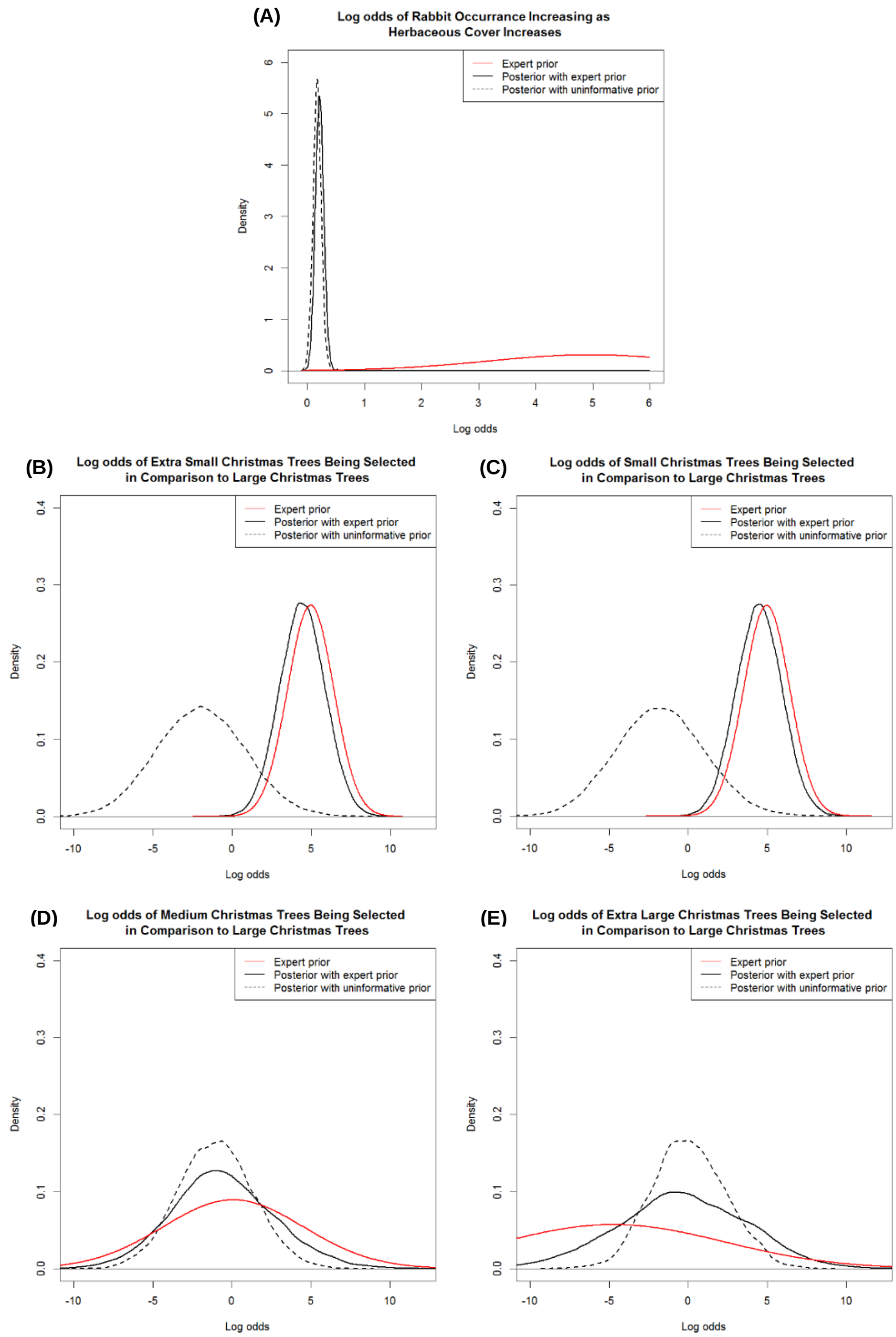

Figure 2. Prior and posterior density functions for a Bayesian mixed effects discrete choice model evaluating eastern cottontail selection of Christmas tree fields and herbaceous cover within their 95% fixed kernel home ranges. Model is comparing use of Christmas tree sizes: *extra-small (B)*, *small (C)*, *medium (D)*, and *extra-large (E)*, and *Herb* (herbaceous cover, *A*) to the use of *large* Christmas trees. Expert elicited priors are shown (red) along with posterior distributions for the model incorporating both the uninformative prior (dashed) and expert prior

Table 1. Uninformative and informative prior and posterior estimates from a Bayesian mixed effects discrete choice model estimating eastern cottontail selection on Christmas tree farms within their 95% fixed kernel home ranges. Informative priors derived through expert elicitation. Table displays differences in cottontail selection of *Christmas tree fields* and *Open fields* over *Hardwoods*. Prior distributions include mean and variance. Posteriors include beta mean estimates and 95% credible interval values.

	Uninformative		**Informative**	
	Prior	Posterior	Prior	Posterior
Christmas Trees	N (0,10)	0.42 (-0.13, 0.99)	N (4.8, 0.31)	4.29 (3.15, 5.43)
Open Fields	N (0,10)	-0.77 (-1.47, -0.05)	N (2.49, 6.18)	2.18 (1.04, 3.32)

Table 2. Uninformative and informative prior and posterior estimates from a Bayesian mixed effects discrete choice model estimating eastern cottontail selection on Christmas tree farms within their 95% fixed kernel home ranges. Informative priors were derived through expert elicitation. Table displays differences in cottontail selection of different Christmas tree sizes (*extra-small*, *small*, *medium*, and *extra-large)* and *Herb* (herbaceous cover) in comparison to *large* Christmas trees. Prior distributions include mean and variance. Posteriors include beta mean estimates and 95% credible interval values.

	Uninformative		**Informative**	
	Prior	Posterior	Prior	Posterior
Herb	N(0,10)	0.18 (0.04, 0.33)	N (4.96, 3.20)	0.21 (0.07, 0.36)
Extra-Small	N(0,10)	-1.79 (-7.17, 3.84)	N (4.96, 2.13)	4.44 (1.62, 7.27)
Small	N(0,10)	-1.60 (-7.12, 3.97)	N (4.96, 2.13)	4.49 (1.68, 7.34)
Medium	N(0,10)	-0.95 (-5.74, 4.07)	N (0.07, 20.79)	-0.56 (-6.79, 6.27)
Extra-Large	N(0,10)	0.14 (-4.57, 5.21)	N (-4.76, 57.61)	-0.52 (-9.24, 7.41)

Table 3. Comparisons of mean squared error (MSE) results from five-fold cross validations run on two Bayesian mixed effects discrete choice models incorporating both uninformative and informative priors. Informative priors created through expert elicitation. *Habitat model* assesses eastern cottontail use of Christmas tree fields and Open Fields in comparison to Hardwoods. *Christmas tree model* compares cottontail use of different Christmas tree sizes (*XS*, *S*, *M*, *XL*) and *Herb* (herbaceous cover) in comparison to large (*L*) Christmas trees

	Habitat Model		**Christmas Tree Model**	
	Uninformative	Informative	Uninformative	Informative
Mean Squared Error (MSE)	46.09	50.21	90.98	100.94

APPENDICES

APPENDIX A

Summary of Individual Cottontail Covariates and Home Range Sizes

Table 1. Home range estimates for 57 eastern cottontails captured on Christmas tree farms in western North Carolina, March-June (2014 and 2015), for which we obtained ≥ 30 VHF telemetry locations. *Animal ID* (individual ID #), *Year* (year captured), *Farm* (farm captured), *Sex*, *# Locations* (# of telemetry locations obtained), and estimates of *95% fixed kernel home ranges* (ha) presented. * 14-042 & 15-019 are the same individual, the only cottontail that survived the entire sampling period.

Animal ID	Year	Farm	Sex	# Locations	95% Fixed Kernel Home Range (ha)
14-025	2014	CS	F	56	6.66
14-030	2014	CS	F	63	1.29
14-034	2014	CS	F	33	3.73
14-026	2014	CS	M	50	3.81
14-027	2014	CS	M	55	6.51
*14-043	2014	GD	F	63	4.56
14-009	2014	GD	M	68	16.02
14-029	2014	GD	M	53	13.70
14-042	2014	GD	M	60	29.75
14-044	2014	GD	M	63	12.78
14-001	2014	MM	F	65	0.99
14-019	2014	MM	F	39	1.36
14-038	2014	MM	F	57	1.24
14-013	2014	MM	M	61	4.27
14-028	2014	MM	M	46	0.90
14-006	2014	OM	F	63	2.07
14-033	2014	OM	F	54	1.62
14-037	2014	OM	F	65	1.60
14-041	2014	OM	F	61	2.85
14-048	2014	OM	M	59	4.56
15-020	2015	CS	F	57	4.97
15-026	2015	CS	F	69	2.26
15-028	2015	CS	F	44	3.82
15-029	2015	CS	F	68	3.25
15-050	2015	CS	F	32	1.26
15-021	2015	CS	M	64	8.71
15-022	2015	CS	M	71	7.46
15-025	2015	CS	M	70	3.00
15-030	2015	CS	M	66	8.57
15-031	2015	DT	F	69	1.76
15-033	2015	DT	F	71	1.46
15-036	2015	DT	F	30	3.68

15-038	2015	DT	F	72	2.16
15-040	2015	DT	F	69	1.91
15-034	2015	DT	M	73	9.37
15-035	2015	DT	M	72	2.77
15-037	2015	DT	M	72	5.14
15-039	2015	DT	M	70	1.99
15-041	2015	DT	M	70	5.60
*15-019	2015	GD	F	77	6.61
15-012	2015	GD	F	77	9.60
15-018	2015	GD	F	77	4.24
15-042	2015	GD	F	65	7.55
15-013	2015	GD	M	77	17.01
15-014	2015	GD	M	79	16.15
15-016	2015	GD	M	72	32.31
15-017	2015	GD	M	72	19.33
15-002	2015	OM	F	78	1.63
15-003	2015	OM	F	76	10.54
15-006	2015	OM	F	80	2.61
15-010	2015	OM	F	75	1.03
15-004	2015	OM	M	79	2.74
15-005	2015	OM	M	45	5.93
15-007	2015	OM	M	76	4.62
15-008	2015	OM	M	78	4.23
15-009	2015	OM	M	80	4.36
15-011	2015	OM	M	76	5.21

APPENDIX B

Home Range Linear Models Candidate Model Set

Table 1. Candidate model set for linear models estimating covariate influence on size of eastern cottontail 95% fixed kernel, breeding season (March-June) home ranges on Christmas tree farms in western North Carolina. We ranked models using Akaike's Information Criterion adjusted for small sample size (AICc). Covariates include: *Sex*, *Year*, *Area* (farm area, ha), *Xmas* (proportion of Christmas tree fields in a home range), and *Herb* (weighted average proportion of herbaceous cover in the home range). We also considered the following interaction: *Xmas**Herb* to account for the relationship between food and cover in determining home range size**.** We included *Null* (null model) representing no effect on home range. *K* indicating the number of estimated parameters, and *AICc* w_i (the Akaike weight).

Model	K	AICc	ΔAICc	AICc w_i
Area + Xmas + Sex + Herb	5	343.66	0	0.51
Area + Xmas + Sex + Herb + Xmas* Herb	6	346.01	2.36	0.16
Area + Xmas + Sex + Herb + Year	6	346.22	2.56	0.14
Area + Xmas + Sex	4	347.53	3.87	0.07
Area + Xmas + Sex + Herb + Year + Xmas*Herb	7	348.69	5.03	0.04
Area + Xmas + Sex + Year	5	349.79	6.13	0.02
Area + Sex + Herb	4	350.88	7.22	0.01
Xmas + Sex + Herb	4	350.95	7.29	0.01
Xmas + Sex	3	352.42	8.76	0.01
Xmas + Sex + Herb + Xmas*Herb	5	353.05	9.39	0
Area + Sex +Herb + Year	5	353.26	9.6	0
Xmas + Sex + Herb + Year	5	353.41	9.75	0
Area + Sex	3	354.21	10.55	0
Xmas + Sex + Year	4	354.7	11.04	0
Xmas + Sex + Herb +Year + Xmas*Herb	6	355.62	11.96	0
Area + Sex + Year	4	356.51	12.85	0
Area + Xmas + Herb	4	357.43	13.77	0
Area + Xmas	3	358.41	14.75	0
Area + Xmas + Herb + Xmas*Herb	5	359.22	15.56	0
Area + Xmas + Herb + Year	5	359.87	16.21	0
Area + Xmas + Year	4	360.74	17.08	0
Area + Xmas + Herb + Year + Xmas*Herb	6	361.78	18.12	0
Xmas	2	362.94	19.28	0
Xmas + Herb	3	363.43	19.77	0
Area + Herb	3	364.37	20.71	0

Xmas + Herb + Xmas*Herb	4	364.91	21.25	0
Area	2	365.08	21.42	0
Xmas + Year	3	365.23	21.57	0
Xmas + Herb + Year	4	365.77	22.11	0
Area + Herb + Year	4	366.61	22.96	0
Xmas + Herb + Year + Xmas*Herb	5	367.37	23.71	0
Area + Year	3	367.38	23.73	0
Sex + Herb	3	367.68	24.02	0
Sex	2	367.69	24.03	0
Sex +Herb + Year	4	369.9	26.24	0
Sex + Year	3	370	26.34	0
Null	1	378.28	34.62	0
Herb	2	379.62	35.96	0
Year	2	380.48	36.82	0
Herb + Year	3	381.71	38.05	0

APPENDIX C

DIC Candidate Model Sets for Bayesian Mixed Effects Discrete Choice Models

Table 1. Candidate model set for a Bayesian mixed effects discrete choice model evaluating selection of habitat on (and around) Christmas tree farms in western North Carolina by eastern cottontails in their 95% fixed kernel, breeding season (March-June) home ranges. Top model selected by deviance information criterion (DIC) outputs evaluating the fixed effect of *Sex* and random effects of *Indiv* (individual) and *Farm*.

Model	Dbar	PD	DIC
Indiv + Farm	1084	209	1293
Indiv	1084	209	1294
Sex + Indiv	1084	210	1294
Sex + Indiv + Farm	1084	210	1294
Sex + Farm	2266	37	2303
Farm	2285	29	2315
Sex	2620	16	2636
Null	2668	8	2676

Table 2. Candidate model set for a Bayesian mixed effects discrete choice model evaluating selection of Christmas tree cover and herbaceous cover on Christmas tree farms in western North Carolina by eastern cottontails in their 95% fixed kernel, breeding season (March-June) home ranges. Top model selected by deviance information criterion (DIC) outputs evaluating the fixed effect of *Sex* and random effects of *Indiv* (individual) and *Farm*.

Model	Dbar	PD	DIC
Sex + Indiv + Farm	4697	58	4755
Indiv + Farm	4697	58	4755
Sex + Indiv	4697	59	4756
Indiv	4697	59	4756
Sex + Farm	7075	19	7094
Farm	7117	15	7132
Sex	7762	9	7771
Null	7825	5	7830

APPENDIX D

Statistical Framework Showing How to Convert Elicited Knowledge into Prior Estimates of Beta Coefficients

To transcribe experts' responses to an estimated beta, we followed the equations published in O'Leary (2008) with a few modifications to account for our experts' higher uncertainty.

For each covariate, $X_j, j = 1, \ldots, J$, the quantity $z_j^{(\ell)}$ represents the elicited response of the ℓth expert, where the elicited response can be the expectation of increase $(z = +1)$, decrease $(z = -1)$, or no substantive change $(z = 0)$ given that all other covariates are held at their optimum. The quantity w_j is the ℓth expert's percentage confidence value for their response for that covariate.

Lower and upper bounds of the beta coefficient, β_j, were defined as $-B$ and B, respectively, such that $|-B| = B$. The value of B can be set based on published data, expert knowledge, or biologically reasonable limits on the values of the regression coefficients. In the absence of suitable data or knowledge, we opted for the last approach, setting $B = 10$.

We represent each expert's response as a mixture of three Gaussian distributions, one for each of the three possible responses (positive, negative, and no substantive change). We make the assumption, for example, if an expert predicts no substantive change with a confidence of 4 (50% confidence of being correct), then the remaining 50% (confidence of being incorrect) can be assigned equally to the expectation of a positive and a negative response. Similarly, if an expert predicts a positive change with a confidence of 6 (93.07%

confidence of being correct), the remaining 6.93% can be assigned, in decreasing proportion, to the expectation of no change and negative change. We assign the constraint that the three confidence probabilities must sum to unity. The equations used to calculate the weights for the three Gaussian distributions are as follows:

When the expectation is no substantive change ($z_j = 0$):

$$w^*_{j,0} = w_{j,0} * \left(\frac{B-1}{B}\right)$$

$$w^*_{j,-1} = w^*_{j,+1} = 0.5 * (1 - w^*_{j,0})$$

When the expectation is a positive change ($z_j = +1$):

$$w^*_{j,-1} = 0.25(1 - w^*_{j,+1})$$

$$w^*_{j,0} = 0.75(1 - w^*_{j,+1})$$

$$w^*_{j,+1} = \left(\frac{B-1}{B}\right) w_{j,+1}$$

When the expectation is a negative change ($z_j = -1$):

$$w^*_{j,-1} = \left(\frac{B-1}{B}\right) w_{j,-1}$$

$$w^*_{j,0} = 0.75(1 - w^*_{j,-1})$$

$$w^*_{j,+1} = 0.25(1 - w^*_{j,-1})$$

After calculating weights for individual's responses, we then combined their response by calculating the average of their weights. In the absence of any reason to treat some individuals as more expert than others, we treated all experts' responses equally, such that the average weight across all experts ℓ for impact m is:

$$\bar{w}_{jm} = \frac{1}{L}\sum_{\ell=1}^{L} w_{jm}^{(\ell)}$$

For each covariate X_j, we calculate the expected β as a mixture of the three distribution components, with each mixture component having parameters θ_j:

$$\beta_j \sim \sum_{m=-1,0,+1} \bar{w}_{jm} p(\beta_j \mid z_j = m, \theta_j)$$

Further, we assume a Normal distribution for each possible impact:

$$p(\beta_j | z_j = m, \theta_j) \sim N(\mu_{jm}, \sigma_{jm}^2)$$

The mean and variance could be based on published data, expert knowledge, or as in our case, set based in reference to the previously set bounds B of beta. Thus, we set the means of the three components as $-\delta = -B/2$, 0, and $\delta = B/2$ for $m = -1,$ 0, and 1, respectively. To calculate the standard deviations, we constrained the cumulative confidence to fall between the endpoints of each component. Thus, for $m = 0$, bounds were $p(-\delta < \beta_j < \delta) = 1 - \alpha$ so that under the Gaussian assumption $\sigma_{j,o} = \delta/\Phi^{-1}(\alpha/2)$. Similarly, for $m = -1$, bounds were $p(-B < \beta_j < 0) = 1 - \alpha$ so that $\sigma_{j,-1} = B/[2\Phi^{-1}(\alpha/2)]$ and for $m = +1$, bounds were $p(-\delta < \beta_j < \delta) = 1 - \alpha$ so that $\sigma_{j,+1} = -B/[2\Phi^{-1}(\alpha/2)]$.

APPENDIX E

Example Illustrating How Expert Knowledge Is Converted to a Beta Coefficient

Question formats to elicit expert knowledge:

1a. As X increases, do you expect Y to show increase/no change/decrease? Or,

1b. Relative to X_{base}, under X_{alt} you expect Y to show increase/no change/decrease?

2. How confident are you that you (integer scale corresponding to odds ratio and percentages) are correct?

Expert A: Increase, with confidence of 5

Expert B: No substantive change, with confidence of 5

Expert C: Increase, with confidence of 4

Set B = 10, δ = 10/2, and α = 0.10. Rescale the confidences and then calculate the average to serve as weights for the three normal distributions.

Expert	**Response (z_j)**	**Confidence (w_j)**	$w^*_{j,-1}$	$w^*_{j,0}$	$w^*_{j,+1}$
A	Increase (+1)	5 (0.7083)	0.09	0.27	0.64
B	No Change (0)	6 (0.9307)	0.08	**0.84**	0.08
C	Increase (+1)	4 (0.5)	0.14	0.41	0.45
	Average ($\bar{w}_{jm}$)		**0.10**	**0.51**	**0.39**

Calculate the combined beta as the sum of the three distributions (negative + neutral + positive): $\beta \sim 0.10N(-\delta, \sigma^2) + 0.51N(0, \sigma^2) + 0.39N(\delta, \sigma^2)$. Plot this combined distribution (red: mean = 0.092, sd = 0.038) and the three component distributions.