University of Kentucky

UKnowledge

Theses and Dissertations--Forestry and Natural Resources

Forestry and Natural Resources

2019

QUANTIFYING WHITE-TAILED DEER DENSITY AND ITS IMPACTS ON AGRICULTURAL SYSTEMS

Jonathan A. Matthews
University of Kentucky, jonathan.matthews@uky.edu
Digital Object Identifier: https://doi.org/10.13023/etd.2019.244

Right click to open a feedback form in a new tab to let us know how this document benefits you.

QUANTIFYING WHITE-TAILED DEER DENSITY AND ITS IMPACTS ON
AGRICULTURAL SYSTEMS

_____

THESIS

_____

A thesis submitted in partial fulfillment of the
requirements for the degree of Master of Science in
Forest and Natural Resource Sciences in the
College of Agriculture, Food and Environment
at the University of Kentucky

By

Jonathan A. Matthews

Lexington, Kentucky

Co- Directors: Dr. Matthew T. Springer, Assistant Extension Professor of Wildlife
Management

and   Dr. John J. Cox, Associate Professor of Wildlife Ecology and Conservation
Biology

Lexington, Kentucky

2019

ABSTRACT OF THESIS

QUANTIFYING WHITE-TAILED DEER DENSITY AND ITS IMPACTS ON
AGRICULTURAL SYSTEMS

White-tailed deer (*Odocoileus virginianus*) commonly consume row crops, with yield losses often attributed to their browsing. Deer density and field morphology may predict yield losses within local areas. We sought to 1) determine the effects of deer browsing on corn and soybean yields and investigate if deer density or field morphology correlated to yield loss in western Kentucky, and 2) compare pellet-based distance sampling to game camera surveys to determine if a distance sampling technique could accurately estimate deer density during the growing season. Overall, deer reduced corn and soybean yields on one-half of surveyed properties. Deer density did not influence yield losses in either crop; however, field morphology correlated with soybean yield losses. Pellet-based distance sampling provided statistically similar estimates as our game camera survey technique; however, at the individual farm level distance sampling estimates proved unreliable. Inaccurate model parameter (i.e., defecation rates) and inability to detect pellet groups in dense vegetation complicated the reliability of distance sampling models. Overall, yield losses from deer occur in western Kentucky and may be a localized event. Finally, game camera surveys should be used over pellet-based distance sampling during the growing season until detection issues and inaccurate model parameters are solved.

KEYWORDS: White-tailed deer, Crop Damage, Deer Density, Population Estimates, Game Cameras, Distance Sampling

Jonathan A. Matthews

(Name of Student)

06/10/2019

Date

QUANTIFYING WHITE-TAILED DEER DENSITY AND ITS IMPACTS ON
AGRICULTURAL SYSTEMS

By
Jonathan A. Matthews

Matthew T. Springer
Co-Director of Thesis

John J. Cox
Co-Director of Thesis

Steven J. Price
Director of Graduate Studies

06/14/2019
Date

ACKNOWLEDGEMENTS

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1. THE EFFECTS OF DEER DENSITY ON CORN AND SOYBEAN YIELDS IN
WESTERN KENTUCKY

ABSTRACT

In the U.S., corn (*Zea mays*) and soybean (*Glycine max*) are two abundantly grown food crops. White-tailed deer (*Odocoileus virginanus*) commonly consume these crops when available, and yield losses are often attributed to their browsing. Recent research suggests that deer may not have as negative of an impact on crop yields as previously thought. Deer density has been suggested as a predictor of damage within local areas; however, the link between deer density and crop damage is not well-established. We sought to determine the effects of deer browsing on corn and soybean yields, investigate if deer density correlated to yield loss, and determine if field morphology could predict where deer-related crop loss would occur in western Kentucky. We estimated deer impacts on crop yields by systematically assigning 1 of 2 treatments (i.e., protected and no protection) to plots in 3 distance classes (10m, 30m, and 50m) from a wooded field edge during the growing season. We established and harvested 282 plots of corn across five farms and 432 plots of soybeans across 7 farms in 2017 and 2018 combined. Deer density was estimated with the Jacobson et al. (1997) branch-antlered buck method. Overall, deer reduced corn and soybean yields on one-half of farms. Deer density did not influence yield losses for either crop. Field morphology could predict soybean yield loss, but not corn yield loss. With small fields commonly being planted in western Kentucky, soybean yield losses from deer may be a localized event depending on field morphology, while corn yield losses my depend on other factors not considered in this study.

INTRODUCTION

Worldwide, humans have attributed agricultural yield losses in a variety of crops to wildlife damage. (McDowell and Pillsbury 1959, Sullivan and Sullivan 1988, Conover and Decker 1991, Naughton-Treves 1998, Herrero et al. 2006, Trdan and Vidrih 2008). The United States Department of Agriculture (USDA) (2002) estimated that total

agricultural damages from wildlife are approximately $1 billion annually in the United States (U.S.), with two-thirds of those damages occurring within field-crop production. Ungulates, in particular, damage crops through browsing and feeding. Specifically, in North America, white-tailed deer (*Odocoileus virginanus*; hereafter, deer) are a major source of agricultural damage (Caslick and Decker 1979, Conover and Decker 1991, Herrero et al. 2006, DeVault et al. 2007a, Trdan and Vidrih 2008, Springer et al. 2013). Corn and soybeans are two field crops most often damaged by deer browsing, and these crops have been increasing in production since the 1990s (Decalesta and Schwendeman 1978, Wywialowski 1996, DeVault et al 2007a, USDA 2016). In 2017, producers in the U.S. planted approximately 237 million acres of field crops with about 90 million acres each of both corn and soybeans making up the vast majority of field crops planted (USDA 2017a). Specifically in Kentucky, producers harvested 2 million acres of soybeans and 1.2 million acres of corn in 2017, most of which occurred in the western half of the state (USDA 2017b). Furthermore, although production is at a high level within Kentucky, input costs are also high and profit margins are narrow for producers; consequently, economic losses from wildlife damage to crops could imperil the viability of some producers (Halich 2019).

Deer browse soybean plants consistently throughout the growing season and have been identified as a primary source of depredation (DeVault et al. 2007a, Colligan 2011). Browse to early-growth-stage plants typically reduces vegetative growth because young plants have more difficulty compensating for biomass removal (Colligan 2011, Rogerson et al. 2014, Hinton et al. 2017). Decalesta and Schwendeman (1978) and Garrison and Lewis (1987) thought that this vegetative reduction could cause yield loss; however, neither study actually measured soybean yields. Once researchers began to measure yield loss associated with deer browsing, they concluded that deer browsing caused no significant yield losses despite vegetative growth reduction, and can even increase yields, probably due to compensatory growth (Colligan et al. 2011, Rogerson et al. 2014, Hinton et al. 2017).

Like soybeans, deer also browse corn, with yield losses estimated to range from 10-75% (Wywialowski 1996, Tzilkowski et al. 2002, DeVault et al. 2007a). Differing from soybeans, most damage and browse pressure to corn occurs during late vegetative

(tasseling) and reproductive (silking and blistering) growth stages (Tzilkowski et al. 2002). Deer have been shown to decrease silage yield (Stewart et al. 2007), although effects to grain yields have been inconclusive (Wywialowski 1996, Tzilkowski et al. 2002, DeVault et al. 2007a). In addition to effects on yield quantity, deer, like many other herbivores (Brooks and Raun 1965, Maine and Boyle 2015), may also affect corn yield quality. Corn quality is measured when sold, and low quality corn earns lower prices. The larval stage of corn earworms (*Helicoverpa zea*) feed upon corn leaves and ears and reduce crop value as a vector for introducing fungal pathogens, such as *Aspergillus flavus,* to infect corn ears (Fennel et al. 1975). *Aspergillus flavus* produces a toxin (aflatoxin) as a metabolic by-product, which stays on the corn ear and is harmful to livestock (Diekman and Green 1992). It is unknown if deer browsing on corn has the same potential to increase aflatoxin presence in corn and contribute to yield losses.

The majority of crop depredation by deer occurs within the first 10m of the field edge, especially near wooded edges where woodlands offer escape cover for wildlife (Garrison and Lewis 1987, Wywialowski 1996, DeVault et al. 2007a). Hinton et al. (2017) found that other environmental factors (competition with other plants at field edges, proximity to forest, and wind damage to outer plants) could impact plant growth at field edges and be mistaken for deer browsing because farmers generally assess crop damage and loss via observation from edges.   (Smathers et al. 1993, Johnson et al 2000, Humberg et al. 2007). This perception of damage may be unintentionally overexaggerated especially in fields surrounded by woods (Tzilkowski et al. 2002, Hinton et al. 2017). If producers are overestimating crop damage then wildlife management strategies are potentially responding to inaccurate producer estimates. Therefore, understanding the extent and causal agents of crop damage to best inform crop and wildlife management is important.

High deer density has been shown to negatively affect ecological communities (Rooney 2009, Russell et al. 2017); however, studies of the effects of deer density on agricultural crops are few and crop-specific impacts are not well understood (Tzilkowski et al. 2002, DeVault et al. 2007a, Hinton et al. 2017). Previous studies have suggested a possible correlation between crop yields and local deer density on a farm, but did not

attempt to quantify that relationship (Stewart et al. 2006, Colligan 2011, Springer et al. 2013, Rogerson et al. 2014).

Field size has also been suggested as a predictor of yield loss ((Decalesta and Schwendeman 1978, Retamosa et al. 2008). Retamosa et al. (2008) found that field morphology could predict wildlife damage to crops, with field size better predicting wildlife-related corn damage, while soybean yield loss was best predicted by field composition (i.e., amount of forested area surrounding fields). However, Retamoa et al. (2008) did not quantify whether wildlife damage was actually causing yield loss in the surveyed fields.

Though wildlife damage to crops, especially from deer, has been well studied, results on yield losses have been conflicting and often implicate other regional or local factors (Decalesta and Schwendeman 1978, Garrison and Lewis 1987, Tzilkowski et al. 2002, DeVault et al. 2007a, Hinton et al. 2017) . Therefore, there is a need to assess any potential effect on yield losses at a local level. Any perceived or real issues occurring between deer browsing/density and crop damage may become more important during years of poor growing conditions and of low grain prices. We used an arrangement of protected and unprotected plots in crop fields in conjunction with deer density estimates and field size measurements to 1) determine the effects of deer on corn and soybean yields in western Kentucky, 2) characterize the relationship between deer density and crop yield loss, 3) characterize the relationship between field size and crop yield loss. We hypothesized that we would see yield reductions in both crops, that yields of both corn and soybeans (full-season and double-crop) would be negatively correlated with deer density, and that field size would predict deer-related yield losses in both crops.

STUDY SITE

We identified candidate farms in five counties of western Kentucky typical of the farming landscape and deer management practices of this region. (Figure 1.1). Farms ranged in size from 40-354 ha and were located in Kentucky deer hunting Zone 1 (KDFWR 2018) which allowed for the harvest of one buck and unlimited does. Five of the six farms were privately-owned and one leased land to hunters. All of the privately-

owned farms were a mixture of crop fields and woodlands, while the 6th farm was owned by the University of Kentucky (UK) and had a mixture of crop fields, woodlands, and pasture land. The UK farm did not allow hunting; however, it was sufficiently small (400 ha) that deer were likely to venture onto adjacent lands with hunting pressure. Soybean field size varied from 2.1- to 102 hectares, while corn field size ranged 0.4 – 102 ha. Average field size was 21.7 ha, the median field size was 4.9 ha, and two-thirds of fields were less than 10 ha. Two types of soybean systems were evaluated for yield losses: full-season and double-crop. Full-season soybeans have only one crop planted in a field per year; whereas, double-crop soybeans have 2 crops (wheat, (*Triticum spp.*) followed by soybeans) harvested in the same calendar year.

During 2017, growing conditions were favorable for grain crops with record yields for soybeans and above average yields of corn (USDA 2017b). During 2018, planting was delayed for some producers in the region due to heavy spring precipitation; however, near record yields were recorded (USDA 2019).

METHODS

YIELD ESTIMATION

We selected six farms in 2017 and 2018 to estimate the impacts of deer on corn and soybean yields. We had 12 fields across the 6 farms over 2 years. The university farm had 2 fields (one of each crop) each year; whereas, all other farms had one field each year. Overall, we had 5 fields of corn, 4 of full-season soybeans, and 3 of double-crop soybeans.

Our study followed the designs of previous studies that estimated deer impacts on crop yields (Colligan 2011, Springer et al. 2013, Rogerson et al. 2014). Fields chosen had a wooded field edge and were greater than 100 m wide to accommodate plot arrangements in all farms except two. The field edges on Farms 1 and 5 in 2018 could only accommodate 60% of the plot arrangement used on other farms. Plot arrangements would estimate crop yields and deer-related yield effects in a field by averaging together individual plots. Plots were 1m^2 areas in the crop field spatially arranged to account for variation in field conditions. Plots were placed linearly, parallel, in three distance-classes

from the wooded field edge (10m, 30m, 50m) (Figure 1.2). The plots were divided equally amongst these three distance-classes (i.e., each distance-class had the same number of plots) with centers 4.4 meters from the others in each distance class. Due to the high occurrence of small production fields in western Kentucky, in 2018, we included a narrow field of full season soybeans surrounded by forested land with high perceived damage (Farm 4, Figure 1.1). This field could not accommodate the 50m distance class, so we doubled the number of plots in the 10m distance class. Additionally, one of the corn fields in 2018 was a small 0.4 ha field, adjacent to soybean fields (Farm 4, Figure 1.1). Plots were established after planting, but before emergence of crops. We protected half the plots in each distance class from deer browsing by encircling them with a 1.22m tall wire fence measuring approximately 7.62m in circumference. The treatment status (protected or no protection) of a plot was randomly determined by flipping a corn at the first plot of every distance class and then alternating the protection status of the subsequent 19 plots in that distance class (Figure 1.2). Fences were large enough to deter deer from browsing the plots; however, allowed for use by other wildlife species (i.e., rabbits, voles, groundhogs, raccoons, etc.) so that protected plots still had the same probability of use by other wildlife species as unprotected plots. Regardless, we saw no other impacts from other wildlife species within our plots. The fences remained until the plots were hand-harvested once the plants matured. Distance classes and alternating plot arrangement accounted for variation of deer browsing within each field. Only the center $1m^2$ of protected plots was harvested. Whole corn ears were harvested and shucked in the field, while soybean plants were stripped of pods. Harvested soybean pods were dried and then threshed using a hand-fed belt thresher. Yields were quantified in eared corn and threshed soybeans.

Additionally, we tested for deer-related effects on quality of corn grain via aflatoxin presence. In 2017, we tested corn samples from the 10-meter distance class for aflatoxin. The 10-meter distance class was chosen due to budget limitations and the assumption this distance class would be the most likely to be browsed. Testing was done at the University of Kentucky Veterinarian Diagnostic Laboratory using High Performance Liquid Chromatography (HPLC) with fluorescence detection with a

minimum level of quantification at 10 ppb for aflatoxins (Scudamore and Hetmanski 1992).

In total, we had 282 corn plots on 5 farms (60 plots on 4, and 42 plots on the fifth), 240 full-season soybean plots across 4 farms (60 plots all fields), and 192 double-crop soybeans across 3 farms (96, 60 and 36 plots respectively).

To determine any effects on yields from deer browse we used a linear regression in Program R blocking on farm with the interaction effects of protection status and distance class with an alpha level set at $p = 0.1$. Aflatoxin results were analyzed using a generalized linear regression with a Poisson distribution in Program R with alpha at $p = 0.05$

DEER DENSITY

Deer density on each property was measured both years using the Jacobson et al. (1997) method for censusing white-tailed deer. The Jacobson et al. (1997) method is a 2-week, baited camera survey, that relies on uniquely-identifiable, branch-antlered bucks and number of deer occurrences to estimate a local deer population. Game cameras were gridded out on properties with one camera per 45 hectares with the game camera located in the center of the grid accounting for natural corridors and trails. Camera surveys were pre-baited with shelled corn for 4-5 days and rebaited with corn every 3-4 days during the 2 week survey as needed. Cameras were set to take one picture with a triggering delay of one minute. Deer density effects on crop yield losses were analyzed using a linear regression blocking by field, with severity of yield loss as the response variable to deer density per farm each year with an alpha level of 0.1. Yield loss severity was categorized into 3 classes (i.e., no damage, low damage, and high damage). No damage fields were those with an alpha level greater than 0.1 from the yield estimation results. Low damage fields had an alpha level lower than 0.1 with percent yield loss less than or equal to 15 percent for soybeans or 20 percent for corn. High damage fields were those with an alpha level lower than 0.1 with percent yield loss greater than 15 percent for soybeans and 20 percent for corn.

FIELD MORPHOLOGY

Field size was measured as the area of the field where our plots were located divided by the perimeter of said field. Field size effects on crop yield losses were analyzed using a linear regression blocking by field, with severity of yield loss as the response variable to the area/perimeter of each field with an alpha level of 0.1. Yield loss severity was categorized the same as deer density analysis.

RESULTS

YIELD ESTIMATION

Deer browse was detected within our study area on all farms both years, but effects on yields were variable. Crop losses from deer browse ranged from $0 - 1002$ kg/ha ($0 - 14.9$ bu/ac) for soybeans, and $0 - 55701$ kg/ha ($0 - 71$ bu/ac) for corn. Yields in general were positively correlated with distance from a wooded edge on nine farms, and negatively correlated with distance from a wooded edge on one farm (Table 1.1, 1.2, and 1.3).

Deer browsing reduced corn yield on Farm 2 in 2017 ($p = 0.057$; Table 1.1 and1.4) and Farm 3 in both 2017 and 2018 ($p = 0.1, 0.004$; Table 1.1 and 1.4). Farm 2 lost 1538 kg/ha (19.6 bu/ac), and Farm 3 lost 1491 kg/ha (19 bu/ac) and 5571 kg/ha (71 bu/ac) respectively each year. Yields for Farm 1 were not impacted either year ($p = 0.79, 0.26$; Table 1.1 and 1.4). Additionally, we found no impact from deer on aflatoxin presence in eared corn ($p = 0.72$).

Deer browsing reduced full-season soybean yields on two farms (Table 1.2 and 1.5). Yields decreased on Farm 1 both years ($p = 0.02, 0.001$), and Farm 2 in 2018 ($p = 0.055$; Table 1.2 and 1.5). Magnitude of loss was 505 kg/ha (7.5 bu/ac), 1002 kg/ha (14.9 bu/ac), and 202 kg/ha (3 bu/ac) for Farm 1 2017, Farm 1 2018, and Farm 2 2018, respectively. Farm 3 had no reduction in full-season soybean yields ($p = 0.46$).

Deer decreased double-crop soybean yields on Farm 4 only in both 2017 and 2018 ($p = 0.05, 0.04$; Table 1.3 and 1.5). Yields on Farm 4 were reduced by 552 kg/ha (8.2 bu/ac) and 505 kg/ha (7.5 bu/ac) in 2017 and 2018 respectively. Farm 5 had no yield

reductions (p = 0.67; Table 1.3 and 1.5). Deer densities on the farms varied from 17 to 39 deer/km2, and from 19 to 55 deer per km2 in 2017 and 2018, respectively (Table 1.4 and 1.5).

Crop yields increased with distance from the wooded field edge for nine fields: corn yields on Farm 1 in both years (p = 0.003, 0.10; r = 0.43, 0.54; Table 1.1), corn yields on Farm 2 in 2017 (p = 0.004; r = 0.39; Table 1.1), corn yields on Farm 3 in 2018 (p = 0.02; r = 0.31; Table 1.1), full-season soybean yields on Farm 1 in 2017 (p < 0.001; r = 0.40; Table 1.2), full-season soybeans on Farm 3 (p = 0.08; r = 0.34; Table 1.2), double-crop soybean yields on Farm 4 both years (p = 0.02, 0.09; r = 0.33, 0.39; Table 1.3) and on Farm 5 (p = 0.003; r = 0.62; Table 1.3). Crop yields decreased with distance from the wooded field edge for Farm 1 in 2018 (p = 0.08; r = -0.01; Table 1.2). Treatment type and distance from a wooded edge interacted at Farm 1 in 2017 (p = 0.07; Table 1.2).

DEER DENSITY EFFECTS ON YIELD LOSS

Deer density was unrelated to both corn and soybean yield losses (Figure 1.3 and 1.4).

FIELD MORPHOLOGY AND YIELD LOSS

Field size could predict deer-related soybean yield losses (p=0.07, r = 0.71), but not corn yield losses (Figure 1.5 and 1.6).

DISCUSSION

Unlike recent findings from grain-crop-deer-damage studies (Rogerson et al. 2014, Hinton et al. 2017), we observed that deer reduced corn and soybean yields, and in some instances the reduction was extreme (i.e., 70% reduction in soybean yields, and 55% reduction in corn yields). Additionally, deer damage did not affect corn grain quality. The hypothesis proposed in other studies that deer density might correlate to yield losses was not confirmed for either crop. Finally, the hypothesis that field size could

9

predict yield losses was confirmed for soybeans, but not for corn (Stewart et al. 2006, Colligan et al. 2011, Springer et al. 2013, Rogerson et al. 2014).

Corn and soybean yield losses were found to vary across farms. Yield losses to corn from deer damage varied from 0 – 5571 kg/ha (0-71 bu/ac), supporting previous research (Wywialowski 1996, Tzilkowski et al. 2002). The magnitude of yield losses were far greater this study than those estimated by Wywialowski (1996) and Tzilkowski et al. (2002). We observed variability in soybean yield losses from deer from 0 – 1002 kg/ha (0-14.9 bu/ac) in full season soybeans and 0-538 kg/ha (0-8 bu/ac) in double-crop soybeans. These observations contradict other research that observed no impact from deer on soybean yields (Colligan et al. 2011, Rogerson et al. 2014, Hinton et al. 2017). The smallest corn field and narrow soybean field in 2018 experienced the greatest losses. Field size may explain yield loss in the soybean field, whereas other factors not considered in the study could be influencing corn yield loss in the small field. Disparity in yield losses of both crops among farms indicates a high potential variability of deer damage.

Deer reduced both corn and soybean yields; however, quality of corn grain (i.e., aflatoxin presence) was not impacted by deer. Herbivory, has been shown to increase aflatoxin presence in corn (Brooks and Raun 1965, Fennel et al. 1975); however, studies have focused heavily on insect vectors of aflatoxin producing fungi. Crop quality has been shown to vary with drought and temperature and therefore, could vary with other environmental stressors such as deer browsing (Dornbos Jr. and Mullen 1992); nonetheless, reduction in grain quality from mammalian herbivory has not been documented (Holman et al 2009, Springer et al. 2013).

Crop yields vary spatially throughout fields, as does deer browsing pressure, and one can often be confused with the other (DeVault et al. 2007a, Retamosa et al. 2008, Hinton et al. 2017). One full-season soybean field (Farm 1, Table 2) had a positive correlation between deer-caused yield losses and distance from a wooded field edge in 2017 (i.e., yield loss from deer decreased as distance increase from a wooded edge). The nine other fields where yields of both crops increased spatially with distance class (i.e., distance from a wooded edge) had no interaction between treatment and distance class; thus the spatial variability in yields was not due to deer. For these nine fields, reduction in

10

yields might be due to environmental or edge effects. Since three of these nine fields did not experience yield reductions from deer, effects from deer must be separated from environmental effects, or producers could incorrectly perceive deer-related yield losses that are not present (Rogerson et al. 2014, Hinton et al. 2017).

One-half of surveyed farms had deer damage consistent across years. The three farms with yield losses from deer in 2017 had yield losses from deer in 2018; the farm with no losses in 2017 had none in 2018. Producers on four of our six farms had complained of deer damage issues in the past, with half of those having yield losses; thus, there is a need to accurately assess producer complaints.

Our findings indicated that deer density is not a useful predictor of corn or soybean yield losses; however, it should be noted that sample size in our correlation analysis of density to yield loss was small. Deer densities on farms in this study (17-55 deer/km2) were similar or higher than most other reported studies evaluating crop damage (Springer et al. 2013, 13 deer/km2 ; Colligan et al. 2011 and Rogerson et al. 2014, 21 deer/km2), but none observed the magnitude of crop yield losses in this study. If deer density truly does not relates to crop yield loses, the current management strategy of lowering deer density on farms will not provide a solution to deer-related yield reductions. Kentucky statute KRS 150:170 allows producers to protect crops from depredation throughout the growing season by removing wildlife upon issuance of a nuisance (damage) permit to an affected landowner. Moreover, western Kentucky has some of the most liberal deer hunting regulations in the state, allowing further reduction of local deer populations outside of the growing season (KDFWR 2018). However, the focus by wildlife agencies on deer removal from farms appears to be the wrong approach since deer density does not correlate to yield losses.

We predicted that smaller fields might have increased yields loss from deer since these fields have greater edge effect (i.e., there is less interior that is buffered from the perimeter). Our field morphology results indicate that for soybean production field area divided by field perimeter may predict deer-related yield losses. This contrasts Rogerson et al. (2014) and Hinton et al. (2017) who observed no reduction in yield to soybeans in small fields despite vegetative reductions, with fields ranging from 8 – 20 and 7.3 – 25.7 hectares, respectively. For corn, Tzilkowski et al. (2002) suggested that crop losses would

be greater in small fields, but we could not confirm that in this study. Tzilkowski et al. (2002) documented reductions in corn yields in field averaging 2.5 hectares, similar to the median field size in our study. Our results fit into original observations that smaller soybean fields were receiving more heavy browse pressure from deer, and thus, more damage (Flyger and Thoeric 1962, Decalesta and Schwendeman 1978, Garrison and Lewis 1984). DeVault et al. (2007b) found that intensity of crop damage to both corn and soybeans increased as field size decreased and the proportion of the field perimeter to forested area increased. Our confirmation that soybean yield loss by deer correlated with field size could be because soybean fields have little cover for deer and small fields offer safety in the form of quick escape into cover (DeVault et al. 2007, Retamosa et al. 2008). Corn fields on the contrary offer cover for deer as well as food since plants are full grown when deer primarily feed upon them (DeVault et al, 2007a, Stewart et al. 2007, Retamosa et al. 2008). Consequently, deer utilization of corn fields may not be as size relevant as soybean fields since corn fields, large or small, may offer a higher sense of security for deer. Other factors not considered in this study that may influence deer use of, and subsequent yield loss in, crop fields may be habitat availability (i.e., amount of forested area), available food, and other field morphological factors (i.e., field shape) (DeVault et al. 2007a, Retamosa et al. 2008).

Environmental and economic conditions may influence producer attitudes towards, and perceptions of, deer damage. Our yield losses occurred in years of good growing conditions. Therefore, in years of poor growing conditions yield losses may be higher due to increased environmental stress on crops and potentially higher deer browse pressure on the crops from less availability of alternative food sources like natural browse. (Lashley and Harper 2012, Hinton et al. 2017). Producer tolerance of deer damage may be lower in years of poor growing conditions, especially if overall yields are reduced due to environmental stress. Moreover, crop prices during our study fell under $10 a bushel for soybeans and $4 a bushel for corn in 2017. In 2018, soybean prices fell further to under $9 a bushel. Overall in Kentucky, many farmers are currently struggling to break even due to low prices and high input costs, thus any reduction in yields have important implications for producers. Consequently, yield losses from deer will be less tolerated when economic stress is high for producers whether it is from poor growing

condition or low grain prices. However, since not all producers saw deer damage equating to yield losses in our study, correctly evaluating damage and losses can be just as important as addressing producer tolerance or deer management tactics.

MANAGEMENT IMPLICATIONS

Crop yield losses occurred at a range of deer densities for both corn and soybeans, but deer density was not correlated to yield losses in either crop. Crop field size could predict soybean yield loss by deer, but not corn yield loss. Field shape and landscape context should be further investigated as predictors of deer damage in in future studies. Current deer management strategies, rely solely on the targeted reduction of deer to reduce density on farms; however, there may be a need to rethink damage management if deer density is truly not a predictor of yield loss. Finally, since farmers are repeatedly planting high impacted areas, management should seek to address local, private farming practices to mitigate yield losses. In certain small fields with heavy use patterns by deer, there may be no practical way to eliminate yield losses.

ACKNOWLEDGMENTS

TABLES

Table 1. 1. Regression Results for Corn Yields.

Results from the linear regression of the interaction between treatment type (i.e., protected from deer browsing or not protected) and distance class for corn yields by farm and year with an alpha level of 0.1. Results shown in kg/ha. Significance of results indicated by asterisk.

Dep. Var.: Yield	Farm 1		Farm 2	Farm 3	
	2017	**2018**	**2017**	**2017**	**2018**
Ind. Var.:	$\bar{x}(\pm SE)^*$	$\bar{x}(\pm SE)^*$	$\bar{x}(\pm SE)^*$	$\bar{x}(\pm SE)^*$	$\bar{x}(\pm SE)^*$
Treatment (Protected)	630.5(±2391.3)	3145.4 (±2541.6)	3798.6 (±1948)*	3420.3 (±2056.5)*	8925 (±2697.6)**
Distance Class	165.4 (±48.7)**	164.3 (±49.9)**	111.2 (±36.1)**	38.3 (±42.6)	126.9 (±51.8)*
Treatment * Distance Class	14.7 (±68.7)	-66.7 (±73.8)	-81.6 (±54.1)	-64.2 (±60.2)	-120.4 (±81.4)

* p = 0.1, **p = 0.05, *** p = 0.001

14

Table 1. 2. Regression for Full-season Soybean Yields.

Results from the linear regression of the interaction between treatment type (i.e., protected from deer browsing or not protected) and distance class for full-season soybean yields by farm and year with an alpha level of 0.1. Results shown in kg/ha. Significance of results indicated by asterisk.

Dep. Var.: Yield	Farm 1		Farm 2	Farm 3
	2017	**2018**	**2018**	**2018**
Ind. Var.:	$\bar{x}(\pm SE)*$	$\bar{x}\ (\pm SE)*$	$\bar{x}\ (\pm SE)*$	$\bar{x}\ (\pm SE)*$
Treatment (Protected)	1370.9 (±552.97)**	1200.0 (±248.8)***	489(±249.2))*	418.9 (±570.3)
Distance Class	42.3(±11.8)***	11.2 (±6.2)*	6.2 (±5.3)	21.3 (±11.8)*
Treatment * Distance Class	-30.1 (±16.4)*	-12.4 (±16.6)	-10.0 (±7.4)	0.57 (±16.7)

* p = 0.1, **p = 0.05, *** p = 0.001

Table 1. 3. Regression Results from Double-crop Soybean Yields.
Results from the linear regression of the interaction between treatment type (i.e., protected from deer browsing or not protected) and distance class for double-crop soybean yields by farm and year with an alpha level of 0.1. Results shown in kg/ha. Significance of results indicated by asterisk.

Dep. Var.: Yield	Farm 4		Farm 5
	2017	**2018**	**2018**
Ind. Var.:	$\bar{x}(\pm SE)$*	$\bar{x}\ (\pm SE)$*	$\bar{x}\ (\pm SE)$*
Treatment (Protected)	631.0(±320.4)*	572.1 (±268.8)**	-286.3 (±673.7)
Distance Class	18.1 (±6.6)**	13.7 (±5.5)**	38.0 (±12.8)*
Treatment * Distance Class	-1.8 (±9.5)	-3.3 (±8.2)	7.4 (±19.1)

* p = 0.1, **p = 0.05, *** p = 0.001

Table 1. 4. Results from Corn Farms.

Corn yields results by farm and year showing yields by treatment in bushels per acre, standard error for yields in bushels per acre, p-values for each field, yield differences in bushels per acre, percent loss of yields for each field, deer density for each farm by year in deer/km2, field perimeter in meters for each field surveyed, and field area in square meters for each field surveyed. Significance of results from our linear regression of corn yields by treatment at alpha level of 0.1 indicated by bolded p-values.

						Corn				
Farm	Year	Treatment	Yield (bu/ac)	SE (bu/ac)	p-value	Yield Difference (P-UP) (bu/ac)	Percent Loss	Deer Density (deer/km^2)	Field Perimeter (m)	Field Area (m^2)
1	2017	Protected	151.7	±11.5	0.79	+ 0.6	-0.4	35	2181	125800
		Unprotected	152.3	±12.1						
	2018	Protected	150.8	±11.5	0.22	- 13.0	3.3	28		
		Unprotected	137.8	±12.6						
2	2017	Protected	84.3	±9.1	**0.06**	- 19.6	23.3	39	4876	1052800
		Unprotected	64.7	±8.2						
3	2017	Protected	110.6	±8.9	**0.1**	- 19.0	17.2	17	748	20500
		Unprotected	91.6	±8.7						
	2018	Protected	120.0	±15.5	**0.004**	- 71.1	55.1	32	287	5300
		Unprotected	48.9	±9.7						

Table 1. 5. Results from Soybean Farms.

Soybean yields results by farm and year showing yields by treatment in bushels per acre, standard error for yields in bushels per acre, p-values for each field, yield differences in bushels per acre, type of soybean planted, percent loss of yields for each field, deer density for each farm by year in deer/km2, field perimeter in meters for each field surveyed, and field area in square meters for each field surveyed. Significance of results from our linear regression of soybean yields by treatment at alpha level of 0.1 indicated by bolded p-values.

Soybeans											
Farm	Year	Treatment	Yield (bu/ac)	StdError (bu/ac)	p-value	Yield Difference (P-UP) (bu/ac)	Type	Percent Loss	Deer Density (deer/km^2)	Field Perimeter (m)	Field Area (m^2)
1	2017	Protected	60.7	±2.5	**0.02**	- 7.4	Full-season	12.9	32	769	26400
		Unprotected	53.3	±3.7							
	2018	Protected	21.0	±1.2	**0.001**	- 14.9	Full-season	70.7	34	989	25000
		Unprotected	6.2	±0.9							
2	2018	Protected	38.1	±1.2	**0.05**	- 2.9	Full-season	7.6	21	4876	1052800
		Unprotected	35.2	±1.3							
3	2018	Protected	62.2	±3.7	0.47	- 6.9	Full-season	11.1	55	1381	245600
		Unprotected	55.3	±2.1							
4	2017	Protected	45.1	±1.9	**0.05**	- 8.2	Double-crop	18.3	17	1966	103800
		Unprotected	36.8	±1.7							
	2018	Protected	23.5	±1.3	**0.04**	- 7.5	Double-crop	32.0	32	749	20500
		Unprotected	16.0	±1.5							
5	2018	Protected	39.6	±4.5	0.67	- 0.7	Double-crop	1.9	19	1385	102000
		Unprotected	38.9	±3.5							

FIGURES
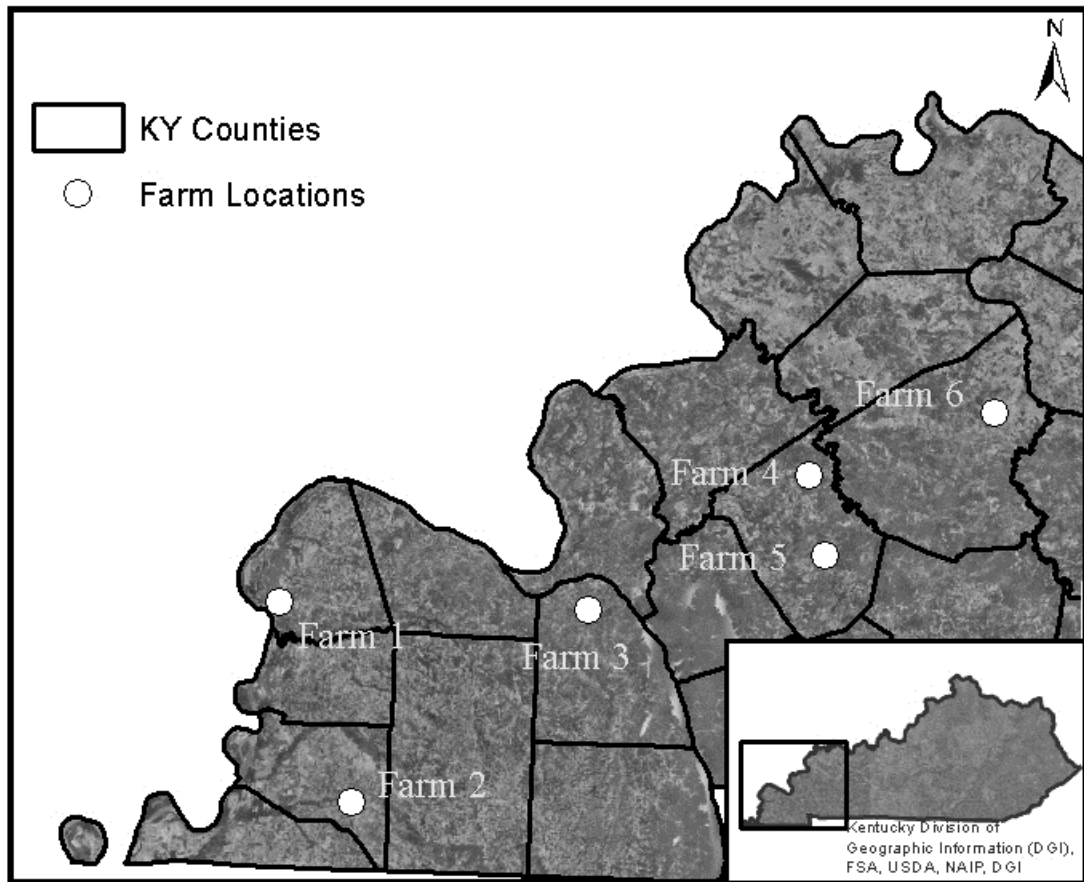
Figure 1. 1. Map of Study Sites.

Map of Study Sites. Map of western Kentucky showing locations of farms used to assess effects of deer browsing corn and soybean yields in 2017 and 2018.
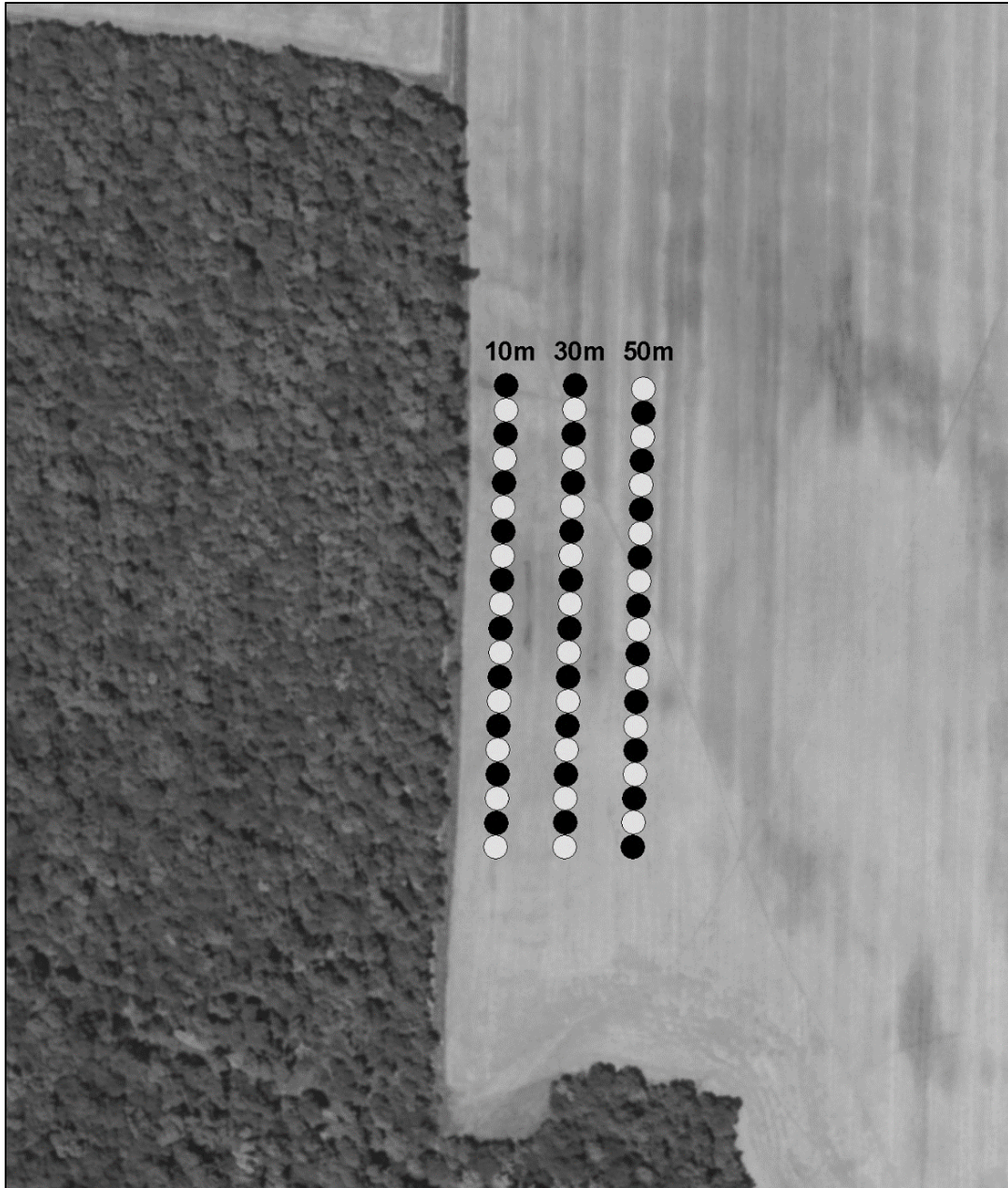
Figure 1. 2. Plot Arrangement

Graphic depiction of plot arrangement used to assess deer-related effects on crop yields. Plots were arranged equally into 3 distance classes parallel to a wooded field edge with treatment (i.e., protected from deer browsing (black) and unprotected (white)) alternating down distance classes.
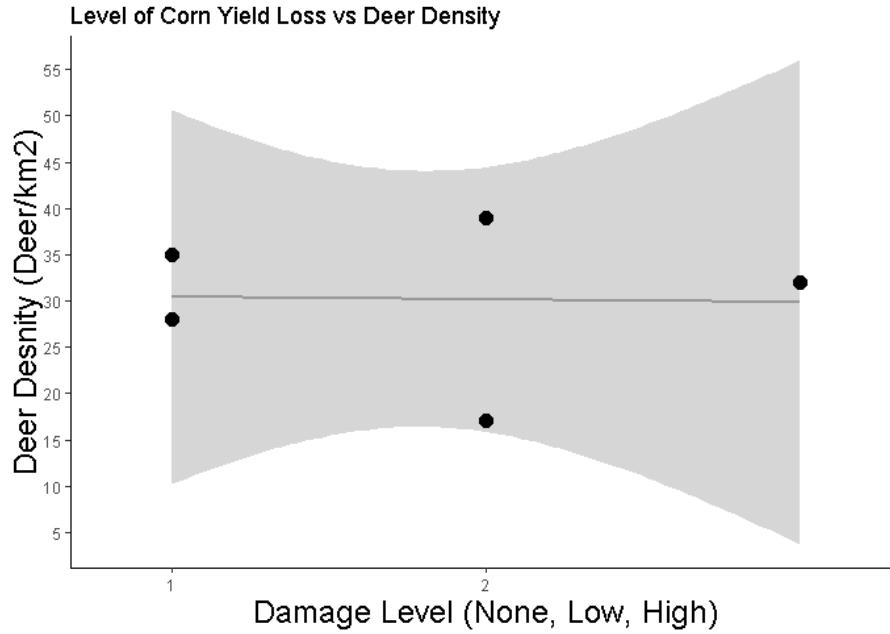
Figure 1. 3. Deer Density vs. Corn Yield Loss

Regression of deer density in deer/km2 and level of corn yield damage from deer by farm including 95% confidence interval. Deer damage was categorized into 3 levels: no yield loss (i.e., p-value >0.1), low yield loss (i.e., p-value <0.1 and percent yield loss ≤ 25), and high yield loss (i.e., p-value < 0.1 and percent yield loss > 25). Deer density did not correlate to corn damage level (p >0.1).
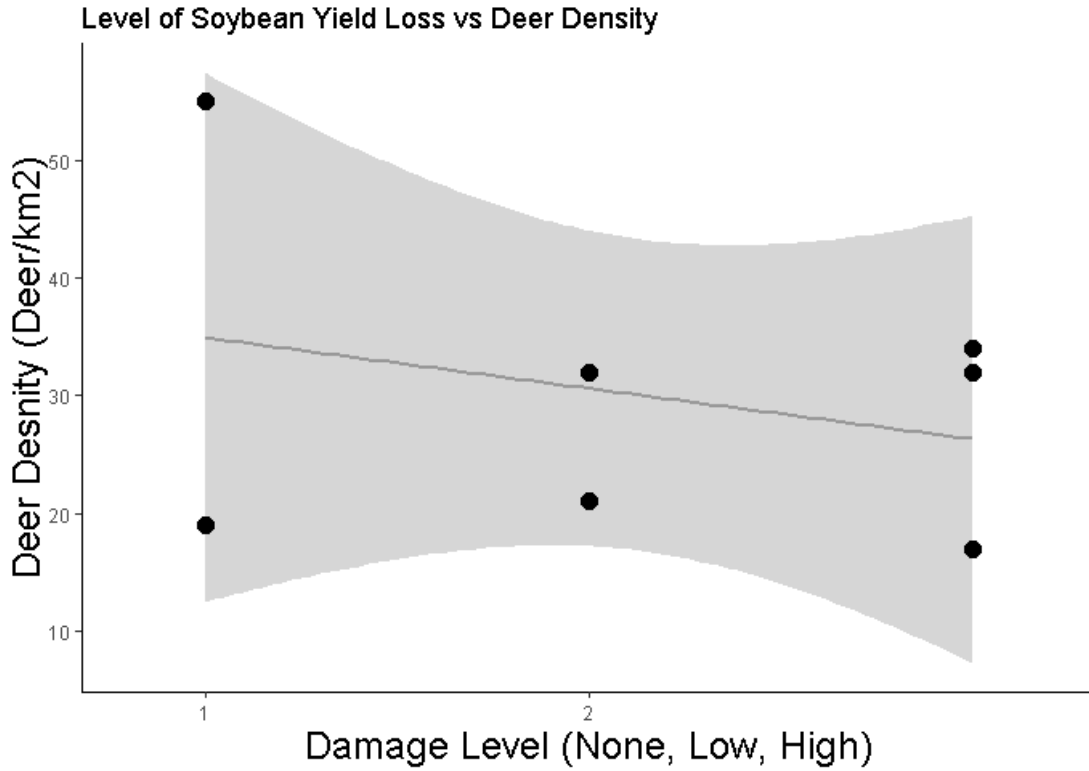
Figure 1. 4. Deer Density vs. Soybean Yield Loss

Regression of deer density in deer/km2 and level of soybean yield damage from deer by farm including 95% confidence interval. Deer damage was categorized into 3 levels: no yield loss (i.e., p-value >0.1), low yield loss (i.e., p-value <0.1 and percent yield loss ≤ 15), and high yield loss (i.e., p-value < 0.1 and percent yield loss > 15). Deer density did not correlate to soybean damage level (p >0.1).
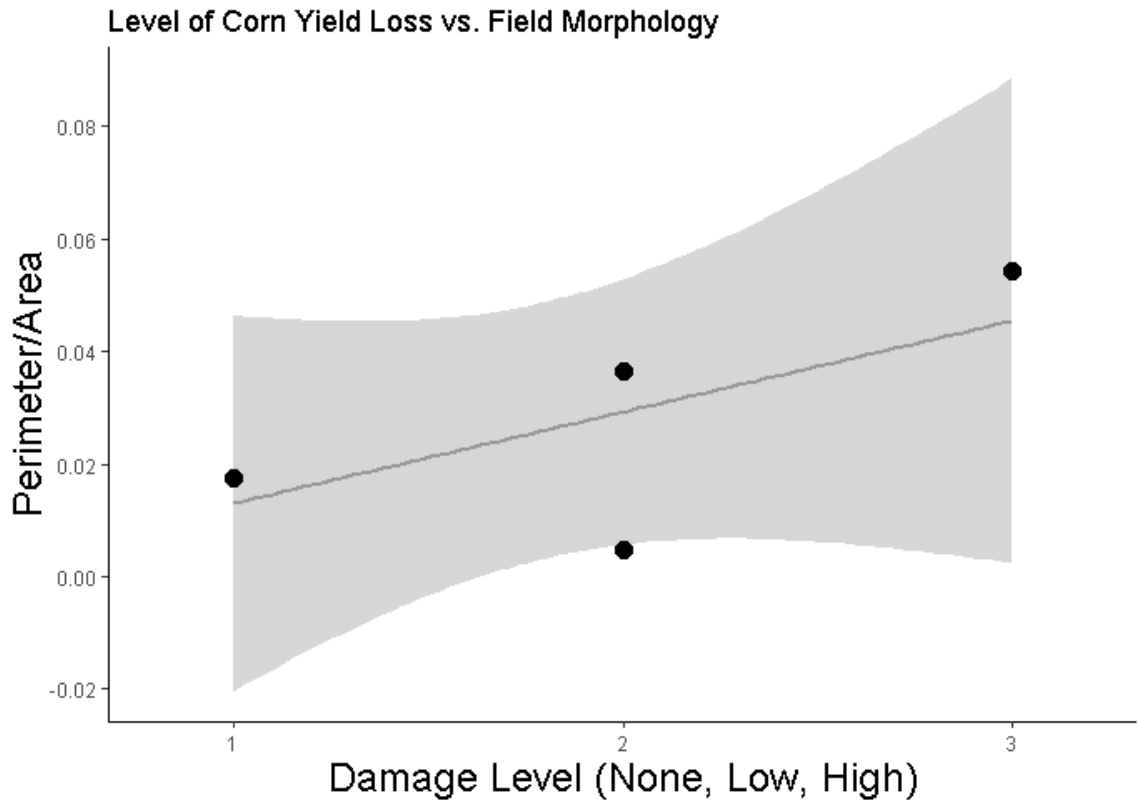
Figure 1. 5. Field Morphology vs. Corn Yield Loss

Regression of the level of corn yield damage by deer and the perimeter/area for each field surveyed including the 95% confidence interval. Deer damage was categorized into 3 levels: no yield loss (i.e., p-value >0.1), low yield loss (i.e., p-value <0.1 and percent yield loss ≤ 25), and high yield loss (i.e., p-value < 0.1 and percent yield loss > 25).
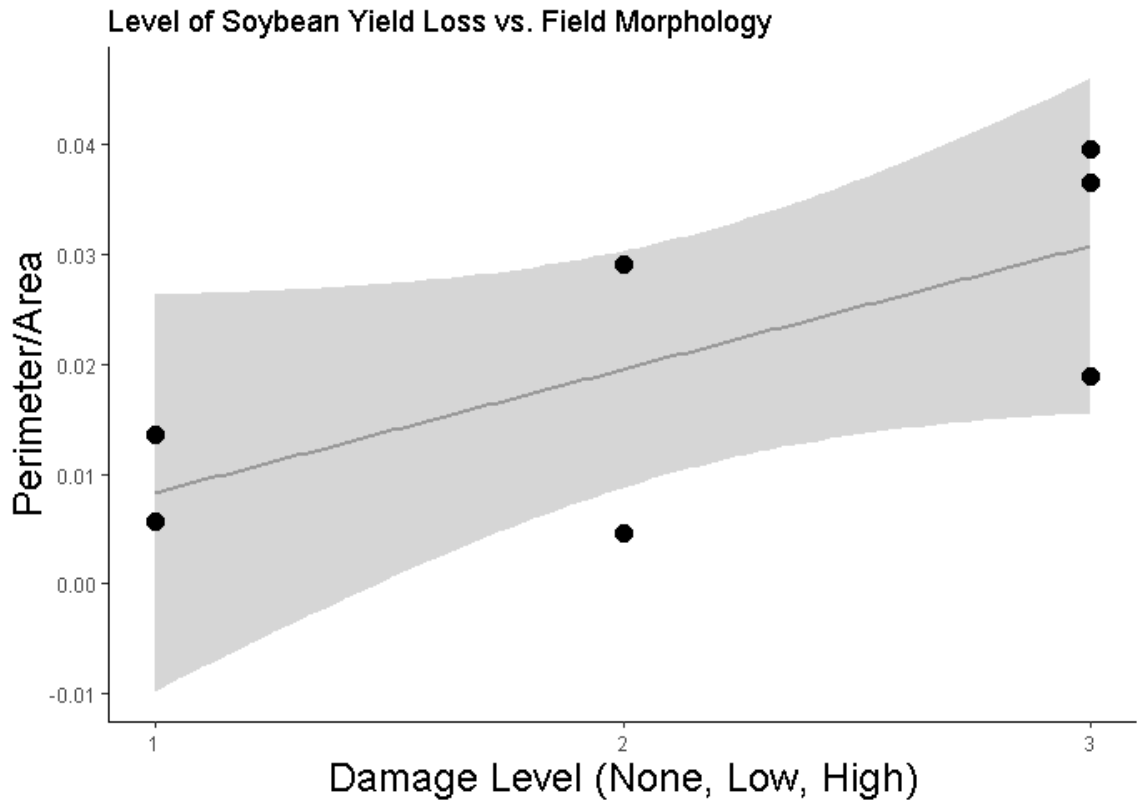
Figure 1. 6. Field Morphology vs. Soybean Yield Loss

Regression of the level of soybean yield damage by deer and the perimeter/area for each field surveyed including the 95% confidence interval. Deer damage was categorized into 3 levels: no yield loss (i.e., p-value >0.1), low yield loss (i.e., p-value <0.1 and percent yield loss ≤ 15), and high yield loss (i.e., p-value < 0.1 and percent yield loss > 15). Perimeter/Area correlated to the level of deer damage to soybeans (p = 0.07, r = 0.71).

CHAPTER 2. PELLETS OR PICTURES: WHICH WOULD YOU PREFER TO COUNT?

ABSTRACT

The ability to accurately measure white-tailed deer (*Odocoileus virginianus*) population density is a valuable tool for wildlife managers; however, generating accurate estimates can be challenging. Due to varying habitat quality, quantity, and other external factors, deer population densities can vary drastically between locations, thereby making local management decisions based on landscape level estimates problematic. Additionally, many common population estimation techniques (i.e., helicopter surveys, FLIR surveys) are expensive to conduct or complicated to perform or analyze and, thus, may not be an option. Trail camera surveys and ground-based distance sampling have proven cost-effective and reliable for estimating deer numbers. Pellet-based distance sampling can provide accurate population estimates in late winter or early spring; however, it has never been tested during summer which could help inform management during the growing and hunting seasons. We evaluated the effectiveness of summer pellet-based distance sampling and generated concurrent population estimates using both the Jacobson et al. (1997) game camera method for estimating white-tailed deer populations and a pellet-based distance sampling technique on 6 farms in western Kentucky during the summers of 2017 and 2018. Game camera surveys were analyzed following Jacobson et al. (1997), while distance sampling results were analyzed using the MCDS function in Program DISTANCE 7.1. Pellet-based distance sampling could provide similar results compared to game camera surveys; however, variation on the individual farm level was high. Additionally, the reliance on accurate model parameters (i.e., defecation rates) and ability to detect pellet groups in dense vegetation complicated the reliability of distance sampling models. Therefore, we would recommend using game camera surveys over pellet-based distance sampling as a pre-harvest technique until detection probability issues are solved and accurate model parameters are determined.

INTRODUCTION

Accurate population estimates are a necessary component of wildlife management (Jenkins and Marchinton 1969). Many site and habitat-specific methods exist to estimate wildlife populations (Drake et al. 2005, Ellis and Bernard 2005, Curtis et al. 2009). Techniques to estimate wildlife populations include aerial surveys, road counts, mark-recapture, harvest reconstruction, point counts, thermal surveys, and infrared surveys. Aerial, thermal, and infrared surveys, along with point and road counts, and mark-recapture are often time-or-cost-prohibited for managers, while harvest reconstruction does not provide current or prognostic population estimates. Robust and accurate population surveys can quickly become costly, have limited applicability due to habitat and species variability, and/or be time-consuming to conduct; hence, accurate population data can be difficult to obtain (Decalesta 2013). Consequently, developing accurate, cost-effective methods to estimate population is a priority and techniques are regularly developed or updated (Polluck 1991, Jacobson et al. 1997, Koerth et al. 1997, Urbanek et al. 2012).

When trying to estimate populations, different wildlife species offer unique challenges including habitat conditions, cryptic nature of species, or low population densities (Miller 1990a, Miller 1990b, Jacobson et al. 1997, van Schaik et al. 2005, Larrucea et al. 2007); consequently, adapting populations estimation techniques to species and location can be a critical challenge for wildlife managers (Marques et al. 2001). Many population surveys rely on detection events (i.e., animal observation, fecal groups, nests, etc.) to generate an estimate (Jacobson et al. 1997, van Schaik et al. 2005, Urbanek et al. 2012). Usually, the higher the probability of detection events, the more accurate the model; therefore, most population models seek to increase detection probability or account for low detection rates (Beringer et al. 1998, Urbanek et al. 2012). Detection probability may differ between estimation techniques depending on a variety of factors (i.e., trap density, timing, habitat, etc.) (Larrucea et al 2007, Wilson et al. 2011). Game species are often a target of wildlife population research since accurate population numbers are needed for effective management decisions because these species' populations are in constant flux due to yearly harvest of the populations. White-tailed deer (*Odocoileus virginianus*; hereafter, deer) are a highly-managed game species; thus,

managers need reliable population estimates (Kilpatrick et al. 1997, Nielsen et al. 1997). Estimating deer populations offers unique challenges such as high habitat variation across its range, large confidence interval ranges for most estimation techniques, and lack of universal cost-effective methods (DeYoung 2011). Deer managers using inaccurate techniques may underestimate or overestimate deer density, which could lead to mismanagement of deer populations (i.e., under-harvest or over-harvest). Under-harvesting deer populations could cause negative ecosystem effects if the population grows too large (Russel et al. 2017), while over-harvest could lead to a population crash. Therefore, obtaining reliable, pre-hunting-season (summer) population estimates for deer is especially critical for determining harvest goals. Previously, varying methods have been evaluated to obtain reliable estimations of free-range deer populations in a variety of habitats (Jacobson et al. 1997, Belant and Seamans 2000, Drake et al. 2005, Urbanek et al. 2012). Convenient, accurate, population estimation techniques have proven difficult to find, as most population techniques (i.e., helicopter counts, spotlight surveys, FLIR surveys, etc.) are filled with biases, are too costly to conduct, or are unreliable depending on location (DeYoung 2011).

Infrared, remote-triggered camera (hereafter, game camera) surveys have been used to monitor and census wildlife populations since their inception (Mace et al. 1994), and reliable population estimates have been generated using game camera surveys (Jacobson et al. 1997, Koerth and Kroll 2000, Larrucea et al. 2007, Moore et al. 2013). Game cameras provide a way to detect wildlife in times or locations that are hard to access, or are difficult to survey (i.e., remote habitat, nighttime, or urban areas; Drake et al. 2005). Game camera surveys require one main assumption to yield confident results: all animals have an equal chance of detection. For deer, Jacobson et al. (1997) produced a relatively-reliable and inexpensive method to estimate localized deer populations using baited game camera surveys and uniquely-identified branch-antlered bucks (hereafter, Jacobson method). Subsequent research determined the Jacobson method to be reliable by evaluating the Jacobson method against other known population estimation techniques and known populations inside enclosures; however, these studies have questioned the equal detectability assumption between sexes (Koerth et al. 1997, Moore et al. 2013). Testing the assumption of equal detectability for the Jacobson method has led to

inconclusive results suggesting that detectability might vary regionally (McKinley et al. 2006, McCoy et al. 2011, Moore et al. 2013). McCoy et al. (2011) found that mature adult male deer in Alabama were less likely to visit bait sites outside of fall, while McKinley et al. (2006) found no bias in detectability of sex for deer in baited game camera surveys in Oklahoma and Mississippi during fall and winter. Other issues with detectability associated with game camera surveys, such as the lack of any measure of uncertainty, have been raised (McCoy et al. 2011, Chitwood et al. 2017). Weckel et al. (2011) tried to assess the lack of uncertainty for parameter estimates for detection issues raised by Curtis et al. (2009), and found that although uncertainty was still broad they could generate more accurate parameter estimates by accounting for trap success of demographic classes. However, regardless of issues raised around detectability, the Jacobson method has been shown to at least produce reliable, albeit conservative, estimates of deer populations (Koerth et al. 1997, Moore et al. 2013). Finally, the Jacobson method is one of the few methods that can estimate pre-hunting-season populations since most other techniques (i.e., helicopter counts, FLIR surveys, fecal counts) are typically conducted in spring or winter during leaf off for maximum visibility by human observers (Koerth et al. 1997, Urbanek et al. 2012).

Another population estimation technique that has been applied to various species, ranging from wild ungulates and bovids to bird populations, is distance sampling (Buckland et al. 1993, Marques et al. 2001, Pérez et al. 2002, Ellis and Bernard 2005, Acevedo et al. 2010, Urbanek et al. 2012). Distance sampling mainly relies on the distance from randomly placed points or lines (transects) to objects of interest (i.e., animals, dung, etc.) to make inferences about a population of unknown size. In distance sampling it is assumed that the detectability of an object decreases with the distance from said object, so much of the population estimates are derived from detection functions which model an observer's probability of detecting an object given its distance from the line/transect or point (Buckland et al. 1993). Detection probabilities are then entered into equations crafted for the specific distance sampling technique and species in order to produce a population estimate.

Pellet-based distance sampling is a distance sampling technique that relies on detection of fecal group clusters along a transect line, along with accurate decay and

defecation rates, to evaluate population numbers and has been used in a variety of habitats and climates on ungulate populations (Buckland et al. 1993, Marques et al. 2001, Ellis and Bernard 2005, Urbanek et al. 2012). Since pellet-based distance sampling detects object clusters, distance from the transect line and cluster size is important into creating accurate detection functions for the data. Distance sampling has 3 main assumptions (Buckland et al. 1993): 1) all objects along the transect line at distance 0 are detected with certainty, 2) objects do not move, and 3) exact measurements are made. In pellet-based distance sampling assumption 1 is addressed by having a recorder follow the observer to ensure complete detection on the line. Furthermore, since one is dealing with sessile pellet groups, assumption 2 is inconsequential and assumption 3 is easily executed. Pellet-based distance sampling also relies on assumptions of consistent defecation rate across individuals; however, defecation rates for deer have been debated in the literature with no clear consensus (Eberhardt and Van Etten 1956, Rogers 1987, Sawyer et al. 1990). Defecation rate and fecal group decay rate are both important to pellet-based distance sampling because without them one cannot transition from a density of pellet groups to density of a deer population; therefore, accurately assessing the fecal group deposition and decay rate is critical to generating reliable deer population estimates.

In the US, pellet-based distance sampling is mainly used for deer in late winter or early spring, especially in the northern states, as pellet groups do not decay throughout the winter and leaf or snow fall gives a relative timeframe for when pellet groups were deposited. (Urbanek et al. 2012, DeCalesta 2013). Pellet-based distance sampling is advantageous because it can still provide robust estimates for population numbers without all pellet groups being detected, and distance sampling requires only limited time to complete surveys (Buckland et al. 1993, Urbanek et al. 2012). Additionally, pellet-based distance sampling uses static objects (fecal groups) to generate populations; therefore, detections can still be made in thick cover (i.e., forests) when visibility is low (Marques et al. 2001, Ellis and Bernard 2005). Urbanek et al. (2012) compared pellet-distance sampling to helicopter surveys of deer and found that pellet-based distance sampling could provide accurate population estimates of deer in late winter and suggested that pellet-based distance sampling could be used at any time of the year. Unlike game

camera surveys; however, pellet-based distance sampling has not been compared to known populations to test that estimates match those of the true population. Furthermore, pellet-based distance sampling has not been evaluated as an estimate of pre-hunting-season (summer) deer populations. Therefore, our objective was to determine if pellet-based distance sampling could provide a reliable, localized, pre-harvest deer population estimate by comparing deer density estimates with those of a game camera survey using the Jacobson method. We predicted pellet-based distance sampling could provide accurate estimates for pre-hunting-season deer populations.

STUDY SITE

All farms surveyed were in western Kentucky, and representative of landscape type and land management practices across the region (Figure 2.1). Deer management practices were also typical for the western Kentucky region. Farms were dominated by row crop fields and woodlands, and farm size ranged from 40-345 hectares. Crop land ranged from 18.7 percent to 90.4 percent of land cover, and forested land ranged from 3.1 percent to 68.8 percent across farms (Table 2.3). Other land cover types on properties were water, developed land, shrub, grassland, pasture land, and wetlands. All other land cover types accounted for less than 12 percent of total land cover on individual farms, except for Farm 5 where pasture land comprised ~one third of the total land cover in addition to high percentages of forest and cropland. In 2017, the survey period was relatively dry, while 2018 saw record setting precipitation (NOAA 2019).

METHODS

In order to compare estimates of pre-hunting-season deer populations using pellet-based distance sampling to game camera surveys using the Jacobson method, we estimated deer densities on private farms in western Kentucky during late summer (July-August). In 2017, we used 4 farms, and in 2018, we added 2 farms to the original 4, for a total of 6 farms in 2018. Once a population estimate was calculated for each farm, estimates from both techniques were standardized across farm by converting farm population to density in deer/km2

Game camera surveys followed the Jacobson branch antlered buck method; whereby, population estimates can be generated using the number of unique branch-antlered bucks identified in images. Cameras were placed in a grid of 1 camera per 45 hectare. Once the grid was set, camera locations were picked close to the center of the grid, but adjusting for natural funnels, travel routes, and trails. Cameras were set to take one picture when triggered with a one minute delay before triggering again.

We pre-baited camera sites for 4-5 days prior to the start of the survey using 100 pounds of corn per site. Surveys lasted 14 days after the pre-baiting period since McKinley et al. (2006) found that with a 14 day baited survey > 90% of deer can be captured. Once surveys began, each site was checked every 4 days and rebaited as needed. Game camera surveys were completed in late July to early August, because antler development is far enough along in Kentucky at that time to ensure accurate identification of individual bucks. For the 4 farms that were surveyed in 2017, the same camera locations were used for 2018.

Once camera surveys were complete, every image from the cameras was analyzed to determine number of deer and class of deer (i.e., branch-antlered buck, spike buck, doe, or fawn) present in each photo. Unique, branch-antlered bucks were identified for each farm. From the camera data, population totals were calculated using the Jacobson et al. (1997) equations based on the number of unique, branch-antlered bucks and occurrences and ratios of deer classes in the camera images for each farm. If deer could not be identified to class in an image, it was excluded.

The Jacobson method uses deer occurrences in images to calculate an estimate for the population as follows: spike-antlered bucks are distinguished from branch-antlered bucks and a ratio of the two buck types is calculated in order to calculate a total estimate of bucks; i.e., $Ps = Nsa / Nba$,

where

Ps = the ratio of spikes to branch-antlered bucks,

Nsa = the total occurrences of spikes captured in the images,

 Nba = the total occurrences of branch-antlered buck captured in the images

and

$Eb = (B \times Ps) + B,$

where

Eb = the estimated number of bucks in the population

B = the number of individually identified branch-antlered bucks.

The estimate of the doe population was calculated using occurrences of all buck and does in images to create a buck:doe ration and using the buck estimate; i.e.,

$Pd = Nd / Nb,$

where

Pd = the ratio of does to bucks in images,

Nd = the total occurrences of does in images,

Nb = the total occurrences of bucks in images (both spikes and branch-antlered),

and

$Ed = Eb \times Pd,$

where

Ed = the estimate for the total deer population within the survey area.

Fawn estimates were calculated similarly to the doe estimate, only using the ratio of does:fawns; i.e.,

$Pf = Nf / Nd$

where

Pf = the ratio of fawns to does,

Nf = the total number of fawn occurrences in the images

and

$Ef = Ed \times Pf,$

where

Ef = the fawn estimate.

The total population estimate was calculated by adding the three estimates together; i.e.,

$Ep = Eb + Ed + Ef,,$

where

Ep is the estimate for the total population.

Distance sampling was performed following techniques in Urbanek et al. (2012) except that we conducted our pellet-based distance sampling in the summer. Farm boundaries were delineated in ArcMap, and then filled with a statistical maximum of 200 meter transects buffered 200 meters from other transects (i.e., transects were not parallel and did not overlap) (Figure 2.3). Transects covered all habitat and land features. Transect numbers ranged from 5-29 transects depending on property area and shape. We used ArcMap to break each transect into 50 m segments to make field navigation easier.

In the field, we started at an end point of each transect and used a compass bearing to walk to the next point on the transect line. A 50m tape was spread between the two points and the observer would walk the line and record any pellet group found within 2 meters on either side of the transect line. Size of group, number of pellets, distance on line, distance from line to the center of the pellet group, whether the pellet group was clumped together or loose pellets, the observer walking the line, and ground cover were recorded for each pellet group found. If pellet groups were dried and crumbling they were considered decayed and not recorded (Urbanek et al. 2012). We walked transects on each property in mid-July, concurrent with the camera surveys in 2017 and the week prior to beginning camera surveys in 2018. Transects on the 4 farms in 2017 were the same transects used on those farms in 2018.

To account for pellet decay, we marked fresh pellet groups (i.e., pellets were black and soft, $n = 10$) and monitored them to determine an average decay rate for our samples (~45 days). Pellet groups were chosen from a variety of habitats and canopy closure conditions, and monitored at every 4-5 days throughout the summer. Pellet decay was complete when pellet groups were dry and crumbling (Urbanek et al. 2012).

Results from pellet-based distance sampling were analyzed using Program DISTANCE 7.1 using the MCDS function to allow for inclusion of covariates. The covariates we included in our models were ground cover, observer, number of pellets, and whether the pellets were in a clump (glob) or loose pellets, and farm on which the surveys were performed. All possible covariates combinations were modeled; however,

the null model of each farm proved to be the best predictor of population density. Program DISTANCE was used to generate a detection probability (f(0)) number for each farm to calculate deer population densities using the Marques et al. (2001) equation:

$$D = \frac{\left(\left(\frac{n}{L}\right) * f(0) * 0.5\right)}{r * s}$$

where D is the deer density estimated for each farm, n is the number of pellet groups detected, L is the length of the transect walked (i.e., 200m), $f(0)$ is the detection probability given by Program DISTANCE, r is the decay rate of pellet groups, and s is the average defecation rate.

Defecation rates in the literature were variable for summer deer herds with some studies suggesting that the often used 13.5 pellet groups/deer/day is too low for deer during summer (Rogers 1987, Sawyer et al 1990, Urbanek et al. 2012). Since we did not have a defecation rate for the region, we ran 3 distances sampling models (DS 1, 2, and 3) per farm using 3 different published defecation rates (13.5, 25, and 34 pellet groups/deer/day) (Eberhardt and Van Etten 1956, Rogers 1987, Sawyer et al. 1990).

ANALYSIS

We entered our data into Program DISTANCE 7.1 as a line transect survey using a cluster of objects, and in 2018 the models were run with two observers. We ran each farm individually modeling all covariate combinations. All covariate models failed to converge at the individual farm level, so the null model for each farm was chosen as the best predictor. Two farms (Farm 1 and 3) were excluded from 2018 due to convergence failure of those individual farms in Program DISTANCE 7.1. These farms lacked a large enough sample size of pellet groups to generate a detection probability (f(0)) even in the null model. The comparison of methods was preformed using a paired t-test with an alpha level of 0.05. Since these are free-ranging deer populations, the comparison between the two methods is not a comparison based on the accuracy of estimating the true population density, but based on the ability of pellet-based distance sampling to yield reliably similar estimates to our game camera surveys.

RESULTS

Game camera survey estimates ranged from 17-55 deer/km^2 (Table 2.1), while distance sampling models varied considerably among models (DS1 = 17-271 deer/km^2, DS2 = 9-146 deer/km^2, and DS3 = 6-107 deer/km^2; Table 2.2). Both Farm 1 and Farm 3 in 2018 did not contain a large enough sample size (n < 10 detections) to generate a distance sampling estimate so they were excluded from comparison analysis. Game camera surveys for these farms estimated deer density on Farm 1 to be 28 deer/km2 and Farm 3 to be 19 deer/km^2.

At low defecation rates, distance sampling model (DS) 1 overestimated deer populations compared to game camera surveys (t = 2.99, df = 7, p = 0.02, Table 2.2). At moderate defecation rates (DS2) there was no difference in pellet-based distance sampling estimates and game camera surveys (t = 2.04, df = 7, p = 0.08). Similarly, at high defecation rates (DS3) there is no difference between the population estimate methods (t = 1.28, df = 7, p = 0.24).

DISCUSSION

We found that game camera surveys produced density estimates consistent with other studies in similar habitat (Stewart et al. 2006, Colligan et al. 2011, Rogerson et al. 2014), while distance sampling estimates were highly variable between and within models. Assuming high defection rates, we found that pellet-based distance sampling does not provide statistically different estimates for deer populations when compared to the population estimates from game camera surveys; however, estimates from one method do not match estimates from the other at the individual farm level. For instance, the highest density farm from the game camera surveys (Farm 2 – 2018) was the 2nd lowest density estimate produced by the distance sampling models (Table 2.2). Low defecation rates used by previous research did not produce a viable model in our study. Small sample size may have had an impact on the results of our comparisons, especially with the convergence failure of 2 farms in 2018 for our pellet-based distance sampling technique.

Population estimates across farms were more similar in game camera surveys (i.e., most deer density estimates were in the 20s and 30s deer/km^2 range) and more variable in pellet-based distance sampling. Game camera survey population estimates varied by 38 deer/km^2 from the highest to lowest density farm (17 – 55 deer/km^2); whereas, the smallest variation between farms in the distance sampling method was model 3 which varied 101 deer/km^2 (6 – 107 deer/km^2). In contrast, Urbanek et al. (2012)'s pellet-based distance sampling population estimates fell within deer density ranges common for white-tailed deer and consistent with similar forested landscapes (12-28 deer/km^2 in 2008 and 15-36 deer/km^2 in 2009) and did not show the high variation that we found in our population estimates (Witham and Jones 1990). The differences we found in the variation of the estimation techniques between farms indicate that there may be a congruity issue with the distance sampling method across farms, possibly due to covariates confounding pellet group detection probability or from inaccurate parameters. Estimates given by pellet-based distance sampling might be improved on farms if model parameters (i.e., defecation rates) are validated and covariates that influence detection of pellet groups are better quantified (i.e., ground visibility, habitat type). We ran a habitat covariate in our models; however, with low sample size of each habitat type (i.e., forest, grassland, etc.) most models failed to converge in Program DISTANCE 7.1, and those that did were not better than the null model for individual farms.

Tracking population trends in an important component of wildlife management, since populations can experience fluctuations throughout time via disease, harvest, habitat conditions, etc. (DeYoung 2011, Stewart et al. 2011). The ability to track population trends between years on individual farms varied between game camera surveys and pellet-based distance sampling. For the 4 farms surveyed both years, 3 produced estimates for pellet-based distance sampling both years, while 1 failed to converge in 2018 (Farm 1). Population trends (i.e., increases or decreases) were the same for both camera surveys and pellet-based distance sampling estimates on 2 of those 3 farms. Farm 6 increased in both surveys, Farm 7 decreased, and Fam 5 increased in camera surveys while decreasing in pellet-based distance sampling estimates (Table 2.2). Therefore, even though small sample size of farms could be a factor in these results, one-third of distance sampling estimates did not track the population trends found in camera

surveys, indicating that pellet-based distance sampling may not be adequate in tracking trends in population as suggested by Urbanek et al. (2012).

These population trends ultimately examine annual changes in population estimates. A reason for variation in population estimates between years on farms may be due to issues with detection (i.e., pellet groups or occurrences of deer are not detected with the same probability each year) or from actual population change. Both pellet-group number and deer occurrences decreased in 2018; however, camera survey estimates rely on ratios of demographic class which offers a buffer from reduced detection numbers in game camera surveys that pellet-based distance sampling does not contain (i.e., a smaller sample size in camera data could still contain accurate proportions of the population and, thus, may still yield reliable results). Moreover, since deer are a popular game animal, management for this species is characterized by both increases and decreases in populations depending on hunter success, management actions, in concert with environmental conditions (Jacobson et al. 2011). Deer are a commonly seen as a pest to agricultural producers and as such population reduction is often a management strategy (Devault et al. 2007). This could explain why farm 6 saw a reduction in deer from 39 deer/km^2 to 21 deer/km^2 from 2017 to 2018; however, the actual harvest and hunting pressure on and around these farms is unknown. In addition, local habitat condition may change from one year to the next causing an ingress or egress of deer to an area that may alter the local deer density. Agricultural crops have shown to alter female deer's home ranges to be closer to crop fields which may explain local increased to deer populations on farms (Vercauteren and Hygnstrom 1998).

Detection of pellet groups was difficult at times in our study, mainly due to ground vegetation, especially in 2018. We found less pellet groups per farm the second year compared to the first on the 4 farms surveyed both years. Lower detections of pellet groups on farms in 2018 was likely due to low visibility from increased ground cover possibly caused by above average precipitation (NOAA 2019). Row crops and cattle pastures additionally hindered our distance sampling surveys both years as visibility in crop fields or un-grazed pastures at times was 0 percent. This led to no pellet group detection along some transects that were completely within crop fields or pastures, which

37

violates the distance sampling assumption that objects of interest along the line at a perpendicular distance of 0 meters have a detection probability of 1.0 (Buckland et al. 1993). On some farms up to 2/3 of the property could not be accurately surveyed due to lack of visibility in agricultural fields, and only on one farm were we able to accurately survey every transect (Farm 3, Figure 2.1). This inability to accurately survey each transect likely caused the convergence failure of one of the two farms in 2018. With too few data points Program DISTANCE is unable to generate a detection probability. An assumption of distance sampling is that all pellet groups in the transect are detected, and although pellet-based distance sampling allows this assumption to be relaxed, in standing soybean fields, almost any detection of pellet groups is impossible at this time of year (Buckland et al. 1993, Urbanek et al. 2012). Therefore, to be a viable, pre-hunting-season or summer population estimation technique, non-winter pellet-based distance sampling needs to account for visibility constraints not found in traditional winter distance sampling. Deer regularly use crop fields to feed, so even though we surveyed available habitat, we were unable to survey high-use area by deer. Based on use alone, we believe it is safe to assume pellet groups are present within these fields even though crop growth may prevent detection.

High deer density did not indicate high detection of pellet groups. We estimated incredibly high deer densities on properties, and still did not detect many pellet groups. Farm 4 in 2017 (Table 2.2) had the highest deer densities out of all of the farms for all distance sampling models, yet we only detected 24 pellet groups with a minimum deer density of 107 deer/km^2 for the lowest model (DS3). The likely reason that we did not observe high number of pellet groups was due to obscurity of pellet groups by vegetation. The effects of this reduced visibility showed up in our effective strip widths generated by DISTANCE 7.1. While we surveyed 2 meters on either side of the transect lines, our effective strip width (i.e., the transect area where we were most effective at detecting pellet groups) was less than 1 meter on either side of the line; therefore, over half of our transect area was not sufficiently surveyed. We do expect that detection would decrease for pellet groups closer to the edge of the transect area, but there should still be some detection along the edges and due to obscurity of pellet groups by ground cover we could not effectively detect those pellet groups (Marques et al. 2001, Urbanek et al. 2012).

While covariates were important to detection, defecation rates also played a role in the accuracy of our distance sampling models. We relied on published defecation rates to use in our models (Eberhardt and Van Etten 1956, Rogers 1987, Sawyer et al. 1990). There is some research to suggest that higher defecation rates are more accurate in summer months than the traditional defecation rate of 13.5 pellet groups/deer/day (Rogers 1987, Sawyer et al. 1990); however, this has not be accurately measured in the southeastern United States. Defecation rates are an important part of pellet-based distance sampling models. If actual defecation rates are higher than assumed, the population estimate will be overestimated since pellet groups assumed to be from different individuals are actually from the same one. Lower defecation rates, such as those given for captive deer in Eberhardt and Van Etten (1956), are typically used in winter pellet-based distance sampling. Even then, both Rogers (1987) and Sawyer et al. (1990) suggest that this winter defection is low. Sawyer et al. (1990) suggests that the original report of 13 pellet groups/deer/day given by Eberhardt and Van Etten (1956) could be low due to the immediate effects of adverse weather (snow storm), while Rogers (1987) suggests that this defection rate may be low due to lack of dietary variation within the pen where the deer were held. Regardless, if these low defecation rates are wrong, any fecal count method will be inaccurate.

In contrast to distance sampling models, game camera survey estimates match more closely with previously reported population estimates for deer in agricultural landscapes (Stewart et al. 2006, Urbanek et al. 2012, Springer et al. 2013). Camera surveys have been proven to be reliable when compared to other methods and when used on a known populations of captive deer (Koerth et al. 1997, Moore et al. 2014); however, although pellet-based distance sampling has been compared to other estimation techniques it has not been replicated using a captive population of known density (Urbanek et al. 2012). Additionally, Jacobson et al. (1997) game camera surveys use branch-antlered bucks to estimate populations, so game camera surveys are regularly used in late summer or early autumn, whereas, pellet-based distance sampling is used mainly in the winter months for deer. Testing summer pellet-based distance sampling on a known, captive population may be important to identifying covariate data that is needed to generate accurate detection functions to use when calculating the population.

If able to provide accurate population estimates, pellet-based distance sampling could provide a less-time-and-money-intensive way to measure localized, pre-hunting-season deer densities. Additionally, if managers simply want to track trends in the population then accurate parameters for distance sampling may not be needed (Urbanek et al. 2012); however, distance sampling did not track these trends in this study. Pellet-based distance sampling takes less time to complete than camera surveys, as pellet-based distance sampling can be completed in one day on even relatively large properties (>350 ha). In addition, distance sampling results can be analyzed in a relatively short time frame, while, in contrast, camera surveys require the sorting of potentially thousands of images.

MANAGEMENT IMPLICATIONS

If choosing a technique to estimate pre-hunting-season populations of deer, camera surveys provide a more reliable method than pellet-based distance sampling. Pellet-based distance sampling did not give consistent or reliable summer deer density estimates in our study. Additionally, camera surveys provide demographic data not given with distance sampling methods. However, if visibility constraints can be solved, if pellet group decay and defecation rates are known, and if no demographic data was needed, pellet-based distance sampling could provide a quicker, more cost-effective method for wildlife managers to assess summer deer populations.

ACKNOWLEDGMENTS

TABLES

Table 2. 1. Camera Survey Results.

Table showing population density estimates from camera surveys by farm in deer/km^2 in 2017 and 2018, along with the property area surveyed in hectares, total occurrences of deer in photos per farm, and the number of unique branch-antlered bucks detected on each farm.

	Farm ID	Property Area (hectares)	Deer/km2	Total Occurrences of Deer	Unique Branch-Antlered Bucks
2017	1	204.4	35	21048	29
	4	126.5	32	28141	21
	5	399.6	17	21048	29
	6	137.4	39	9171	8
2018	1	204.4	28	10520	11
	2	40.2	55	3210	7
	3	41.5	19	2268	4
	4	126.5	34	22663	14
	5	399.6	32	23293	13
	6	137.4	21	4945	8

Table 2. 2. Population Estimates by Method.

Table showing pellet-based distance sampling density estimates with 95% confidence intervals by distance sampling model, farm, and year compared to camera survey estimates in deer/km^2. Distance sampling model 1 overestimated deer populations; whereas, distance sampling models 2 and 3 provided statistically similar estimates to camera surveys.

Farm	DS1 - 13.5 fecal groups/deer/day	DS2 - 25 fecal groups/deer/day	DS3 - 34 fecal groups/deer/day	Camera Surveys
Farm 1 - 2017	170 (126 - 228)	92 (68 - 123)	67 (50 - 91)	35
Farm 2 - 2018	27 (15 - 50)	15 (8 - 28)	11 (6 - 20)	55
Farm 5 - 2017	271 (227 - 323)	146 (123 - 174)	107 (90 - 128)	32
Farm 5 - 2018	122 (93 - 160)	66 (50 - 86)	48 (37 - 63)	34
Farm 6 - 2017	80 (55 - 114)	43 (30 - 62)	32 (22 - 45)	17
Farm 6 - 2018	114 (89 - 144)	61 (48 - 78)	45 (36 - 57)	32
Farm 7 - 2017	197 (154 - 252)	106 (83 - 136)	78 (61 - 100)	39
Farm 7 - 2018	16 (5 - 60)	9 (3 - 27)	6 (2 - 20)	21

Table 2. 3. Property Land Cover Table.

Table showing the land cover percentages for each surveyed property based on the National Land Cover Dataset from 2011. All forest type, developed land, and wetland land cover were combined into broad categories.

PERCENTAGE OF HABITAT TYPE ON FARMS

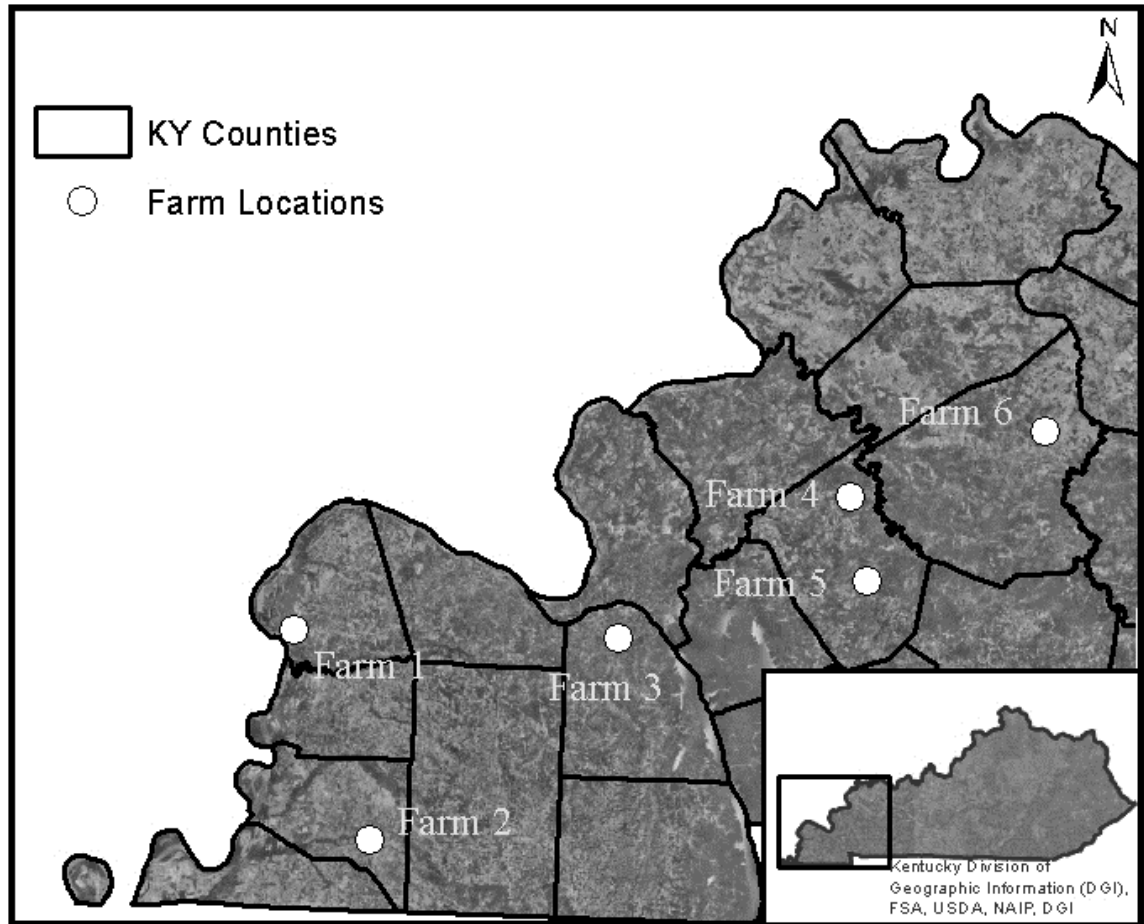| FARM	Water	Developed	Forest	Shrub	Grassland	Pasture	Crops	Wetlands
1	0.2	0.8	51.2	0.2	1.2	--	36.4	10.0
2	--	4.9	3.1	--	--	--	90.4	1.6
3	--	6.6	29.1	--	--	--	64.3	--
4	--	3.4	68.8	--	--	--	22.2	5.6
5	--	4.4	42.3	--	1.0	33.6	18.7	--
6	0.1	4.9	14.7	--	--	3.9	75.0	1.4

FIGURES

Figure 2. 1. Map of Study Sites

Locations of study sites in western Kentucky used to compare pellet-based distance sampling and game camera surveys in 2017 and 2018 showing all 6 farms locations and the counties in which they are found.

Figure 2. 2. Pellet-based Distance Sampling Transects

A map of one farm used in our distance sampling method showing our transect array. Transect are arranged where a statistically maximum number of 200 meter transects randomly placed inside property boundaries buffered 200 meters from other transects will fit into the property boundary.

REFERENCES

Acevedo, P., J. Ferreres, R. Jaroso, M. Durán, M. A. Escudero, J. Marco, and C. Gortázar. 2010. Estimating roe deer abundance from pellet group counts in Spain: An assessment of methods suitable for Mediterranean woodlands. Ecological Indicators 10: 1226-1230.

Belant, J., and T. Seamans. 2000. Comparison of 3 devices to observe white-tailed deer at night. Wildlife Society Bulletin 28: 154-158.

Brooks, D. L., E. S. Raun. 1965. Entomogenous fungi from corn insects in Iowa. Journal of Invertebrate Pathology 7:79-81.

Buckland, S. T., D. R. Anderson, K. P. Burnham, and J. L. Laake. 1993. Distance sampling: estimating abundance of biological populations. Chapman and Hall, London, United Kingdom.

Buckland, S. T., D. R. Anderson, K. P. Burnham, J. L. Laake, D. L. Borchers, and L. Thomas. 2001. Introduction to distance sampling: estimating abundance of biological populations. Oxford University Press, New York, New York, USA.Caslick, J. W., and D. J. Decker. 1979. Economic feasibility of a deer-proof fence for apple orchards. Wildlife Society Bulletin 7:173-175.

Chitwood, M. C., M. A. Lashley, J. C. Kilgo, M. J. Cherry, L. M. Conner, M. Vukovich, H. S. Ray, C. Ruth, R. J. Warren, C. S. Deperno, and C. E. Moorman. 2017. Are camera surveys useful for assessing recruitment in white-tailed deer? Wildlife Biology 1:wlb.00178.

Colligan, G. 2011. Factors affecting white-tailed deer browsing rates on early growth stages of soybean crops. Human-Wildlife Interactions 5:321 -332.

Conover, M. R., and D. J. Decker. 1991. Wildlife damage to crops: perceptions of agricultural and wildlife professionals in 1957 and 1987. Wildlife Society Bulletin 19:46-52.

Curtis, P., B. Boldgiv, P. Mattison, and J. Boulanger. 2009. Estimating deer abundance in suburban areas with infrared-triggered cameras. Human-Wildlife Conflicts 3: 116-128.

Decalesta, D. 2013. Reliability and precision of pellet-group counts for estimating landscape-level deer density. Human - Wildlife Interactions 7: 60-68.

Decalesta, D. S., and D. B. Schwendeman. 1978. Characterization of deer damage to soybean plants. Wildlife Society Bulletin 6:250-253.

DeVault, T., B. Macgowan, J. Beasley, L. Humberg, M. Retamosa, and O. Rhodes. 2007a. Evaluation of corn and soybean damage by wildlife in northern Indiana. Proceedings of the 12th Wildlife Damage Management Conference.

DeVault, T., J. Beasley, L. Humberg, B. Macgowan, M. Retamosa, and O. Rhodes. 2007b. Intrafield patterns of wildlife damage to corn and soybeans in northern Indiana. Human-Wildlife Conflicts 1:205-213.

DeYoung, C. A. 2011. Population dynamics. – In: Hewitt, D. G. (ed.), Biology and management of white-tailed deer. CRC Press, pp. 147–180

Dornbos, D. L., and R. E. Mullen. 1992. Soybean seed protein and oil contents and fatty acid composition adjustments by drought and temperature. Journal of the American Oil Chemists' Society 69:228-231.

Drake, D., C. Aquila, and G. Huntington. 2005. Counting a suburban deer population using Forward-Looking Infrared radar and road counts. Wildlife Society Bulletin 33: 656-661.

Eberhardt, L., and R. C. Van Etten. 1956. Evaluation of the pellet group count as a deer census method. The Journal of Wildlife Management 20: 70-74.

Ellis, A. M., and R. T. F. Bernard. 2005. Estimating the density of kudu (Tragelaphus strepsiceros) in subtropical thicket using line transect surveys of dung and DISTANCE software. African Journal of Ecology 43: 362-368.

Fennell D.I., E. B. Lillehoj, and W. F. Kwolek. 1975. Aspergillus flavus and other fungi associated with insect-damaged field corn. Cereal Chemistry, 52S: 314-321.

Flyger, V., and T. Thoerig. 1962. Crop damage caused by Maryland deer. Proceedings of the Annual Conference of the Southeastern Association of Game and Fish Commissions 16:45- 52.

Garrison, R. L., and J. C. Lewis. 1987. Effects of browsing by white-tailed deer on yields of soybeans. Effects of browsing by white-tailed deer on yields of soybeans 15:555-559.

Halich, G. 2019. Corn and Soybean Budgets – Western Kentucky – 2019. University of Kentucky Department of Agricultural Economics Corn, Soybean and Wheat Budgets.
http://www.uky.edu/Ag/AgriculturalEconomics/halich_greg_rowcropbudgets.php

Herrero, J., A. García-Serrano, S. Couto, V. M. Ortuño, and R. García-González. 2006. Diet of wild boar (*Sus scrofa L*.) and crop damage in an intensive agroecosystem. European Journal of Wildlife Research 52:245-250.

Hinton, G. C., B. K. Strickland, S. Demarais, T. W. Eubank, and P. D. Jones. 2017. Estimation of deer damage to soybean production in eastern Mississippi: Perception versus reality. Wildlife Society Bulletin 41:80-87.

Holman, J. D., C. R. Thompson, R. L. Hale, and A. J. Schlegel. 2009. Grazing effects on yield and quality of hard red and hard white winter wheat. Agronomy Journal 110:775–788.

Humberg, L. A., T. L. DeVault, B. J. MacGowan, J. C. Beasley, and O. E. Rhodes, Jr. 2005. Crop depredation by wildlife in northcentral Indiana. Ninth Proceedings of the National Wild Turkey Symposium.

Jacobson, H. A., C. A. DeYoung, R. W. DeYoung, T. E. Fullbright, and D.G. Hewitt. 2011. Population dynamics. – In: Hewitt, D. G. (ed.), Biology and management of white-tailed deer. CRC Press, pp. 453-479.

Jacobson, H. A., J. C. Kroll, R. W. Browning, B. H. Koerth, and M. H. Conway. 1997. Infrared-triggered cameras for censusing white-tailed deer. Wildlife Society Bulletin 25:547-556.

Jenkins, J. H., and R. K. Marchinton. 1969. Problems in censusing the white-tailed deer. Pages 115-118 in L. K. Halls, ed. White-tailed Deer in the Southern Forest

Habitat: Proceedings of a Symposium. U.S. Forest Service, Southern Forest Experiment Station, New Orleans, La.

Johnson D. L., J. M. Fly, L. Muller. 2000. Landowners' perceptions of white-tailed deer damage to crops in Tennessee. The Ninth Wildlife Damage Management Conference Proceedings.

Kentucky Department of Fish and Wildlife Resources. 2016. 2015-2016 Kentucky Department of Fish and Wildlife Resources white-tailed deer report.

Kentucky Department of Fish and Wildlife Resources. 2018. Kentucky Hunting and Trapping Guide.

Kentucky Revised Statutes (KRS). 2019. Title XII. 150:170.

Kilpatrick, H. J., S. M. Spohr, and G. G. Chasko. 1997. A controlled deer hunt on a state-owned coastal reserve in Connecticut: controversies, strategies, and results. Wildlife Society Bulletin 25:451–456.

Koerth, B. H., and J. C. Kroll. 2000. Bait type and timing for deer counts using cameras triggered by infrared monitors. Wildlife Society Bulletin 28: 630-635.

Koerth, B. H., C. D. McKown, and J. C. Kroll. 1997. Infrared-triggered camera versus helicopter counts of white-tailed deer. Wildlife Society Bulletin 5: 557-562.

Lashley, M. A., and C. A. Harper. 2012. The effects of extreme drought on native forage nutritional quality and white-tailed deer diet selection. Southeastern Naturalist 11:699–710.

Mace, R. D., S. C. Minta, T. L. Manley, AND K. E. Aune. 1994. Estimating grizzly bear population size using camera sightings. Wildlife Society Bulletin 22:74-83.

Marques, F. F. C., S. T. Buckland, D. Goffin, C. E. Dixon, D. L. Borchers, B. A. Mayle, and A. J. Peace. 2001. Estimating deer abundance from line transect surveys of dung: sika deer in southern Scotland. Journal of Applied Ecology 38: 349-363.

Mayle, B. A., J. A. Peace, and R. M. Gill. 1999. How many deer? A field guide to estimating deer population size. Forestry Commission. Edingburgh, UK (Field Book 18).

McCoy, J., S. Ditchkoff, and T. Steury. 2011. Bias associated with baited camera sites for assessing population characteristics of deer. Journal of Wildlife Management 75: 472-477.

McDowell, R. D., and H. W. Pillsbury. 1959. Wildlife damage to crops in the United States. The Journal of Wildlife Management 23:240-241.

McKinley, W. T., S. Demarais, K. L. Gee, and H. A. Jacobson. 2006. Accuracy of the camera technique for estimating white-tailed deer population characteristics. Proceedings of the Annual Conference of the Southeastern Association of Fish and Wildlife Agencies 60: 83-88.

Miller, S. D. 1990a. Population management of bears in North America. International Conference on Bear Research and Management 8:357-373.

Miller, S. D. 1990b. Population management of bears in North America. International Conference on Bear Research and Management 8: 393-404

Moore, M. T., A. M. Foley, C. A. DeYoung, D. G. Hewitt, T. E. Fulbright, and D. A. Draeger. 2013. Evaluation of population estimates of white-tailed deer from

camera survey. Journal of the Southeastern Association of fish and Wildlife Agencies 1:127-132.

Naughton-Treves, L. 1998. Predicting patterns of crop damage by wildlife around Kibale National Park, Uganda. Conservation Biology 12:156-168.

Nielsen, C. K., W. F. Porter, and H. B. Underwood. 1997. An adaptive management approach to controlling suburban deer. Wildlife Society Bulletin 25:470–477.

NOAA NCEI (2019). NOAA National Centers for Environmental Information. Retrieved from http://www.ncdc.noaa.gov/.

Pérez, J. M., E. Serrano, R. Alpízar-Jara, J. E. Granados, and R. C. Soriguer. 2002. The potential of distance sampling methods to estimate abundance of mountain ungulates: review of usefulness and limitations. Pirineos 157: 15-24.

Polluck, K. H. 1991. Modeling capture, recapture, and removal statistics for estimation of demographic parameters for fish and wildlife populations: past, present, and future. Journal of the American Statistical Association 86: 225-238.

Retamosa, M, I., L. A. Humberg, J. C. Beasley, and O. E. Rhodes Jr. 2008. Modeling wildlife damage to crops in northern Indiana. Human–Wildlife Conflicts 2:225–239.

Rogers, L. L. 1987. Seasonal changes in defecation rates of free-ranging white-tailed deer. The Journal of Wildlife Management 51: 330-333.

Rogerson, J., J. Bowman, E. Tymkiw, G. Colligan, and B. Vasilas. 2014. The impacts of white-tailed deer browsing and distance from the forest edge on soybean yield. Wildlife Society Bulletin 38:473-479.

Rooney, T. 2009. High white-tailed deer densities benefit graminoids and contribute to biotic homogenization of forest ground-layer vegetation. Plant Ecology 202:103-111.

Russell, M. B., C. W. Woodall, K. M. Potter, B. F. Walters, G. M. Domke, and C. M. Oswalt. 2017. Interactions between white-tailed deer density and the composition of forest understories in the northern United States. Forest Ecology and Management 384:26-33.

Sawyer, T., R. Marchinton, and W. Maclentz. 1990. Defecation rates of female white-tailed deer in Georgia. Wildlife Society Bulletin 18:16-18.

Scudamore, K., and M. Hetamanski. 1992. Analysis of mycotoxins in cereals and animal feed using a multi-toxin gel permeation chromatography clean-up method. Mycotoxin Research. 8: 37-47.

Smathers, W. M., Jr., G. R. Stratton, and D. Shipes. 1993. Landowners perceptions of crop damage from white-tailed deer in South Carolina. Eastern Wildlife Damage Control Conference 6:160–165.

Springer, M. T., J. L. Bowman, and B. L. Vasilas. 2013. The effect of white-tailed deer browsing on wheat quality and yields in Delaware. Wildlife Society Bulletin 37:155-161.

Stewart, C. M., W. J. McShea, and B. P. Piccolo. 2007. The impact of white-tailed deer on agricultural landscapes in 3 National Historical Parks in Maryland. Journal of Wildlife Management 71:1525-1530.

Stewart, K. M., R. T. Bowyer, and P. J. Weisberg. 2011. Population dynamics. – In: Hewitt, D. G. (ed.), Biology and management of white-tailed deer. CRC Press, pp.181-217.

Sullivan, T. P., and D. S. Sullivan. 1988. Influence of alternative foods on vole populations and damage in apple orchards. Wildlife Society Bulletin 16:170-175.

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

Trdan, S., and M. Vidrih. 2008. Quantifying the damage of red deer (*Cervus elaphus*) grazing on grassland production in southeastern Slovenia. European Journal of Wildlife Research 54:138-141.

Tzilkowski, W. M., M. C. Brittingham, and M. J. Lovallo. 2002. Wildlife damage to corn in Pennsylvania: Farmer and on-the-ground estimates. The Journal of Wildlife Management 66:678-682.

Urbanek, R., C. Nielsen, T. Preuss, and G. Glowacki. 2012. Comparison of aerial surveys and pellet-based distance sampling methods for estimating deer density. Wildlife Society Bulletin 36: 100-106.

USDA Economic Research Service. 2016. Baseline Related Historical Data.

USDA. 2002. U.S. Wildlife Damage. National Agricultural Statistic Service.

USDA. 2017. Acreage. National Agricultural Statistics Service. Released June 30, 2017

USDA. 2017. Kentucky Agricultural Statistics 2017 Annual Bulletin. National Agricultural Statistic Service.

USDA. 2019. Kentucky Agricultural Statistics 2018 State Agigicultural Overview. National Agricultural Statistics Service.

van Schaik, C. P., S. A. Wich, S. S. Utamo, and K. Odom. 2005. A simple alternative to line transects of nests for estimating orangutan densities. Primates 46: 249-254.

Vercauteren, K. C., and S. E. Hygnstrom. 1998. Effects of agricultural activities and hunting on home ranges of female white-tailed deer. The Journal of Wildlife Management 62: 280-285.

Weckel, M., R. Rockwell, and F. Secret. 2011. A modification of Jacobson et al.'s (1997) individual branch-antlered male method for censusing white-tailed deer. Wildlife Society Bulletin 35: 445-451.

Wilson, R. R., J. K. Young, and Shivik, J. 2011. Coyote capture vulnerability relative to space use and trap density. The Journal of Wildlife Management 75: 721-725.

Witham, J. H., and J. M. Jones. 1990. White-tailed deer abundance on metropolitan forest preserves during winter in northeastern Illinois. Wildlife Society Bulletin 18:13–16.

Wywialowski, A. P. 1996. Wildlife damage to field corn in 1993. Wildlife Society Bulletin 24:264-271.

VITA

Educational Institutions attended and degrees already awarded:
University of Kentucky, Bachelor of Science in Natural Resources and Environmental Science

Professional positions held:

Graduate Teaching Assistant, University of Kentucky

Field/Research Technician, University of University of Kentucky

Scholastic and professional honors:

Awards

Forest and Natural Resource Sciences Graduate Student Award for Excellence
2nd Place Poster, 41st Southeast Deer Study Group
Best Presenter, Annual Meeting of the Kentucky Chapter of The Wildlife Society

Grants

2016 University of Kentucky Undergraduate Summer Research Grant

TWS Wildlife Damage Management Working Group Travel Grant

Graduate Student Conference Travel Award - Department of Forest and Natural Resource Sciences Graduate Program

Graduate Student Congress Travel Award

Professional publications:

Black Vulture Effigy Directions. 2018. Matthew T. Springer and Jonathan A. Matthews, University of Kentucky Department of Forestry and Natural Resources Wildlife Extension. FORFS 18-03. https://forestry.ca.uky.edu/files/forfs18-03.pdf

Using Camera Surveys to Estimate White-tailed Deer Populations. 2019. Jonathan A. Matthews and Matthew T. Springer, University of Kentucky Department of Forestry and Natural Resources Wildlife Extension. *In press*.

Jonathan A. Matthews