LANDSCAPE–LEVEL EFFECTS OF WEATHER AND LAND COVER ON WILD TURKEY ABUNDANCE, PRODUCTIVITY, AND REGIONAL HARVEST POTENTIAL IN NEW YORK STATE

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ABSTRACT

LANDSCAPE–LEVEL EFFECTS OF WEATHER AND LAND COVER ON WILD TURKEY ABUNDANCE, PRODUCTIVITY, AND REGIONAL HARVEST POTENTIAL

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Wild turkey populations have been successfully restored across their historic range, and now populations are no longer increasing, but rather are decreasing or have stabilized. New York State has several long-term, state-wide, data sets which provided us a unique opportunity to examine the drivers of productivity, fall harvest, and spring abundance. Landscape-level habitat configuration is the most important factor in supporting levels of productivity. Land-cover proportions and landscape configurations affect mean levels of fall harvest, and higher spring rainfall decreases fall harvest leading to temporal fluctuations. Landscape-level spring population abundance is detrimentally affected by winter severity, is not mitigated by agricultural lands, but is unaffected by fall harvest.

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INTRODUCTION

The ecology of wild turkeys has been of interest to conservationists, managers and researchers alike for over a century due to over-harvest of the species across North America, reaching a low of about 30,000 by the late 1930s. Many aspects of eastern wild turkey biology have undergone investigation, and much of the knowledge that has been gained facilitated the restoration of populations to their historic range and into vegetation communities previously thought to be unsuitable habitat for wild turkeys. Wild turkeys were once thought to be deep forest-dwelling species because the surviving turkey populations of the early 20th century were found in undisturbed old growth forests (Kennamer et al. 1992). In fact, restored wild turkey populations have flourished across wide-spread forest-agriculture landscapes which have provided high-quality habitat consisting of multiple vegetation communities interspersed in an accessible and exploitable pattern on the landscape. The abiotic and biotic environment in which animals survive, disperse, grow, and reproduce is their habitat and is specific to the species (Hall et al. 1997). Quality of habitat is on a continuum and varying levels of quality support survival of individuals, then reproduction, and then population persistence (Hall et al. 1997). The forest-agriculture landscape provides high-quality habitat for eastern wild turkeys (Porter 1992). These landscapes consist of forests and shrub lands with trees for roosting and low cover for nesting habitat (Porter and Gefell 1996). Additionally, grasslands and cultivated fields support essential food resources for the growth and development of young (i.e., poults; Hurst 1992).

The forest-agriculture landscapes of the Great Lakes states and Northeast US, which most of the northern-most populations of wild turkeys inhabit, experience weather conditions unlike other parts of the wild turkey's range. The climate of these regions is colder than most of the remaining range of the eastern wild turkey, and therefore weather is an important driver of populations (Healy 1992). Spring weather impacts nest success, poult survival and, consequently, productivity and fall population size. Winter weather affects body condition, survival, and, consequently, spring population size. Population size determines the number of birds available for hunter harvest during spring and fall harvest seasons.

Past research provided much understanding of wild turkey populations. However, most past studies independently investigated habitat and weather effects on wild turkey populations. Most studies were conducted at small geographic scales (e.g., 4 counties within New York State), and many studies emphasized understanding of drivers of fall populations.

The idea that multiple processes and patterns influence wild turkey demographics is not new. Biologists know that weather and habitat affect nest success and hen survival through predation risk. Adverse weather impacts poult survival, and important brood rearing habitat is essential for poult nutritional requirements. Nest success and poult survival are vital for recruitment and population growth. Porter (2007) advocated for a deeper understanding of the ecology of wild turkeys in northern latitudes. He suggested that weather and habitat do not act alone, but rather there is a more complex interaction relationship, and that the drivers of wild turkey populations appear “to operate at multiple geographic scales (Porter 2007).” Several studies investigated the importance of both weather and habitat (Porter et al. 1980, Vander Haegen et al. 1989, Porter and Gefell 1996). Porter and Gefell (1996) examined the effects of land cover type and many weather variables on fall harvest across southern New York from 1969−81. Porter et al. (1980) examined the effects of winter severity buffered by agricultural food sources in Minnesota, and Vander Haegen et al. (1989) did so in southwest Massachusetts.

However, large scales (i.e., larger than county) and interactions had not been examined explicitly; a different method of assessment was needed to understand how these factors interact to influence wild turkey abundance, productivity, and harvest potential across large spatial scales. I examined habitat and weather and their interactions across multiple large geographic scales. I explored the impacts of habitat and spring weather on fall harvest and productivity to merge multiple independent lines of research. Then I investigated the effects of habitat and winter severity on spring abundance to pool additional independent lines of research. In Chapter 1, I assessed the impacts of landscape composition and configuration and spring rainfall on fall harvest across regional variations of New York State. I examined the interactions of habitat and weather at 2 large spatial scales. In Chapter 2, I investigated the effects of winter severity, fall harvest and landscape composition and configuration, particularly the availability of agricultural lands, on spring abundance. I examined the interactions of winter severity and agriculture at 2 large spatial scales. In Chapter 3, I considered the effects of landscape configuration and spring rainfall on productivity in the highly forested northern region of New York State versus the interspersed landscape of agriculture and woodlands of the southern region. I identified the major drivers, how they interact across multiple spatial scales, and their effects on fall harvest, spring abundance and productivity (Fig I-1).

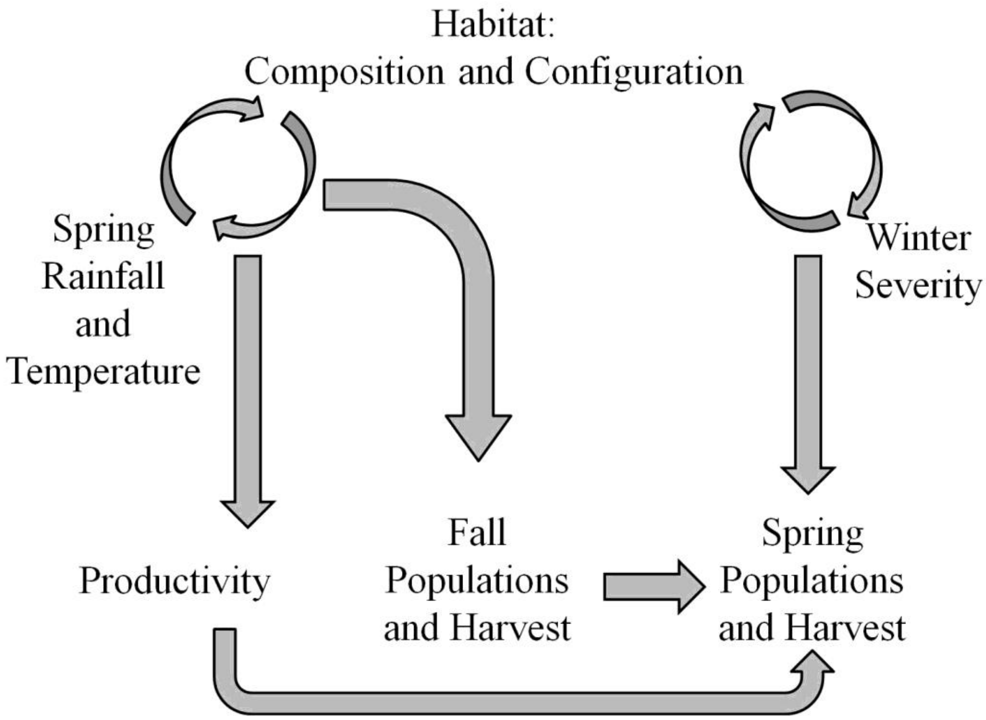

Figure I-1. Conceptual model of ecological drivers of wild turkey productivity, fall populations and harvest and spring populations and harvest. Habitat availability and accessiblity is assessed through landscape-level composition and configuration and supports varying levels of population numbers. Spring rainfall is both a surrogate for predator effects through the moisture-facilitated nest depredation hypothesis and directly affects poult survival. Spring temperature directly influences nest and poult survival, and nest and poult survival impacts productivity and fall populations. Winter severity affects survival and consequently spring populations. Weather drives annual population fluctuations. There are interactions between weather and habitat affecting productivity and populations differently depending on habitat. Productivity and fall harvest may affect spring populations.

The results from this study contribute to the body of scientific knowledge about how habitat and weather influence wild turkey population size and productivity, while explicitly addressing interactions at large spatial extents and across long periods of time. Important environmental drivers vary in their effects depending on landscapes and annual variability of climatic factors. Knowledge of these drivers, and how they interact, gives managers the power to make more informed management decisions to impact turkey populations and harvest sustainability. There are some drivers over which managers have no control; management of other drivers across large spatial scales can be prohibitive. However, knowing the important drivers of turkey populations allows managers to adjust regulations to the harvest potential of populations thereby minimizing impacts from drivers that they cannot affect.

CHAPTER 1: LANDSCAPE-LEVEL PATTERNS AFFECT REGIONAL WILD TURKEY FALL HARVEST

ABSTRACT

Management goals for wild turkey (*Meleagris gallopavo*) populations have shifted from stocking populations toward creating opportunities for sustainable harvest of populations. Populations that were once increasing are now either declining or stabilizing into a pattern of fluctuating abundance. This change in population growth has prompted managers to re-examine potential factors driving populations and subsequent harvest opportunities and re-evaluate harvest regulations to better compensate for ecological drivers beyond their control. Our objective was to identify ecological factors that drive harvest. We evaluated the roles of habitat and weather in driving fall harvest numbers using 26 years of harvest data for 891 townships in New York State. We estimated fall harvest using the negative binomial distribution in mixed effects models, incorporating ecological variables as independent explanatory variables and effort as an offset in the models. The random effects varied by year and township, and the fixed effects were standardized and included land-cover composition and configuration metrics and total May and June rainfall. We used AIC to chose the most parsimonious among competing models. Our results showed that there were a few major drivers across the state. Harvest decreased with increasing spring rainfall across agricultural landscapes ($\beta = -0.117$, 95% CI = −0.22 to −0.014), mixed landscapes of northern hardwood forests and agriculture ($\beta = -0.145$, 95% CI = −0.223 to −0.067), northern hardwood and oak dominated forests interspersed with agricultural operations ($\beta = -0.094$, 95% CI = −0.156 to −0.033), and agricultural river valleys ($\beta = -0.162$, 95% CI = −0.256 to −0.067). As comparitively low proportions of land-cover types increased, harvest increased. The increasing proportion of open lands in the northern hardwood forests was positively associated with increasing harvest ($\beta = 0.257$, 95% CI = 0.095 to 0.419), while the increasing proportion of mixed forest in the agricultural river valleys was positively associated

with increased harvest (β = 0.43, 95% CI = 0.218 to 0.641). Forest edges and interspersion and juxtaposition of different cover types affected harvest positively in climate-ecozones where there is a dominant cover type (e.g., in the heavily forested areas, increasing interspersion of cover types increased harvest; β = 0.49, 95% CI = 0.327 to 0.653). We showed that across different climate-ecozones there was not one suite of drivers of harvest, but rather a few common drivers and many regionally-distinct drivers. Understanding the relationships between environmental variables and harvest across a landscape allows managers to predict harvest and balance regulations with environmental drivers that cannot be controlled.

KEY WORDS

harvest, habitat, land-cover configuration, *Meleagris gallopavo silvestris*, New York State, population index, spring weather

INTRODUCTION

Management of wild turkeys has moved beyond restoration toward development of sustainable harvest opportunities. In the mid to late 20th century, management actions had restored eastern wild turkey populations to places across their known historic range and beyond. Establishment of eastern wild turkeys into places beyond their historic range and into environments heavily modified by agriculture occurred as a result of experimental translocation and research that suggested these places were suitable (Kennamer et al. 1992). Once-increasing populations are now experiencing fluctuations and declines of unequal magnitudes across large geographic extents (Tapley et al. 2011). This fluctuation is causing concern about the potential of wild turkey populations to continue supporting current levels of hunting pressure. Managers are recognizing a need to re-examine factors driving populations and harvest numbers.

Modern harvest seasons, beginning in the 1960s, were implemented in a restoration management environment of growing wild turkey populations (M. Schiavone, New York State Department of Environmental Conservation, personal communication). The current within-state delineations of harvest regulations were set with limited information about the drivers of populations and harvest. Alternatively, they are a product of biologists' experiences with staggered population reintroductions, ecoregional landscape differences, and relative hunter interest. Past research shows that eastern wild turkey populations are driven by spring weather (Healy 1992, Roberts et al. 1996, Roberts and Porter 2000) and landscape-scale habitat (Glennon and Porter 1999, Porter and Gefell 1996). Managers sought to tailor new harvest regulations more specifically to how ecological drivers affect the regional potential for harvest opportunity. Now, the long track record of experience and data offer an opportunity to better understand the factors driving harvest potential and thus sustainability. However, no studies to date have attempted to integrate weather and habitat to explore how these might interact to drive harvest.

Spring weather affects nest success and poult survival (Healy 1992, Roberts and Porter 1998a;b). Generally low nest success (Vangilder 1992) and higher hen predation rates during nesting (Speake 1980) are exacerbated by higher May rainfall (Roberts and Porter 1998b). The likely underlying mechanism is that nest predators learn olfactory cues that lead them to a nest (Miller and Leopold 1992). In the Northeast and Midwest U.S., poult survival is also negatively affected by rainfall (Healy and Neno 1985, Roberts and Porter 1998a, Rolley et al. 1998); large poults that cannot shelter beneath the hen suffer mortality when exposed to moisture and cool temperatures. The linkage of weather and nest success, and nest success and fall populations, allowed Roberts and Porter (2000) to successfully use weather to predict fall harvest in southwestern New York; similar links between weather and recruitment into fall populations were also seen in Wisconsin (Rolley et al. 1998). Therefore, we predicted that higher total average May and June rainfall would reduce harvest.

Landscape-scale habitat characteristics also have proven useful predictors of fall populations and fall harvest because of their influences on risk of nest predation and abundance. Fleming (2003) demonstrated that when habitat was viewed at a scale larger than nest site and forest patch, landscape-level (i.e., 78 km^2) edge density, in both fragmented and contiguous landscapes, was a critical parameter. Specifically, she noted that abrupt edges increased nest predation risk, while increased shape complexity of patches decreased nest predation risk. The consequence would be decreased harvest in townships with more abrupt edges and increased harvest in townships with more complex shapes. More generally, the ability to find forage, cover, and roosting habitat in the mixed landscapes of agriculture and northern hardwood and oak-hickory forests in the East, and agriculture and oak-hickory forests in the Midwest is affected by landscape composition and configuration (Gefell 1991, Lewis 1992, Wunz and Pack 1992, Glennon and Porter 1999). Consequently, we predicted varying relationships between landscape composition metrics and harvest because the ideal proportions of open land and agriculture to forested land differ across the range of the eastern wild turkey. In 3 southwestern counties of New York, Glennon and Porter (1999) found that high edge density, increasing proportions of open cover, and high interspersion correlated with high numbers of harvested birds. In concordance with these studies, we predicted that the various landscape configuration metrics all increased harvest. However, we also hypothesized non-linear relationships between habitat measures and harvest; we predicted land-cover configuration metrics that quantify increasing landscape complexity will increase harvest up to a certain level, above which the landscape will be too fragmented to be considered good habitat and would thus reduce harvest.

While these studies of responses of wild turkeys to weather and habitat have reshaped our thinking about the drivers of abundance levels, little work has been done to evaluate how weather and habitat might interact. Our objectives were to (1) identify the major large-scale habitat and weather factors driving relative abundance of wild turkeys that are subsequently available for harvest and (2) determine if and how the drivers interact. New York State provides a valuable system for understanding how populations and harvest vary in response to spring weather across heterogeneous landscapes because the New York State Department of Environmental Conservation (NYS DEC) has long-term, state-wide, fine-resolution township-level data spanning 26 years and 918 townships.

STUDY AREA

The state of New York is diverse both in its climate and in its landscapes. New York can be divided into 6 climate regions (Thompson 1966). The Adirondacks and Tug Hill experience cold winters with persistent snow, and summers are cool and wet. The St. Lawrence Plain and Champlain Valley, while at similar latitudes to the Adirondacks are lower in altitude than the Adirondacks, and Champlain Valley sits in a precipitation shadow cast by the Adirondack topography resulting in cold drier winters and cool drier summers. The Great Lakes Plain, Finger Lakes and parts of the Central Appalachians experience lake-effect snow in the winter and summers that are warm and dry. The Cattaraugus Highlands and Allegheny Hills in the southwest, parts of the Central Appalachians, the Eastern Appalachian Plateau, and the Taconic Highlands also experience snowy and cold winters and summers that are cool and wet. The Hudson River Valley and the intersections of the Mohawk and Hudson River Valleys are considered a transition zone that experiences variable climate located between climate regions of high precipitation. The Hudson Highlands, Triassic Lowlands, Manhattan Hills, and Coastal Lowlands have winters that are mild and wet and summers that are warm and humid.

The ecoregions of New York State fall along slightly different delineations (Bailey 1995). The Northern Appalachian-Boreal Forest (i.e., Adirondacks and Tug Hill) is mostly a landscape of evergreen forests. The St. Lawrence Plain and Champlain Valley are fairly flat landscapes with many wetland types. The Great Lakes Plain, as well as the Finger Lakes, Mohawk River Valley and the Cattaraugus Highlands consist of a majority of agricultural landscapes on flat plains and lightly rolling low landscapes. The Finger Lakes support many vineyards; the Cattaraugus Highlands have dairy farms interspersed among northern hardwood forests, and the Mohawk River Valley is a corridor of high urbanization. The Western Allegheny Plateau (i.e., Allegheny Hills) is mostly forested in northern hardwood with agricultural operations interspersed. The High Allegheny (i.e., Central and Eastern Appalachian) Plateau is comprised of a mixture of northern hardwood and oak-dominated forests inhabiting slopes with dairy farms lying in the valleys. Historically, there has been a higher concentration of dairy in the eastern compared to the central part of this ecoregion (Thompson 1966). Lower New England – Northern Piedmont (i.e., Taconic Highlands, Hudson River Valley, Hudson Highlands, Triassic Lowlands, and Manhattan Hills) highlands are comprised of northern hardwood and oak forests while the lowlands consist of river valleys and dense urbanization. The North Atlantic Coast (i.e., Coastal Lowlands) is highly urbanized around New York City but less so on Long Island which supports shrubby upland habitats and low-lying coastal wetlands.

The delineations of climate regions and ecoregions lie along very similar lines. We combined the climate regions and the ecoregion delineations into 7 study areas alike in both climate and eco-geography that we call climate-ecozones: Southwest, Central Appalachians, Eastern Appalachians and Taconic Hills, Hudson and Mohawk River Valleys, Great Lakes Plain, Adirondacks and Tug Hill, and St. Lawrence Plain and Champlain Valley (Fig 1-1).

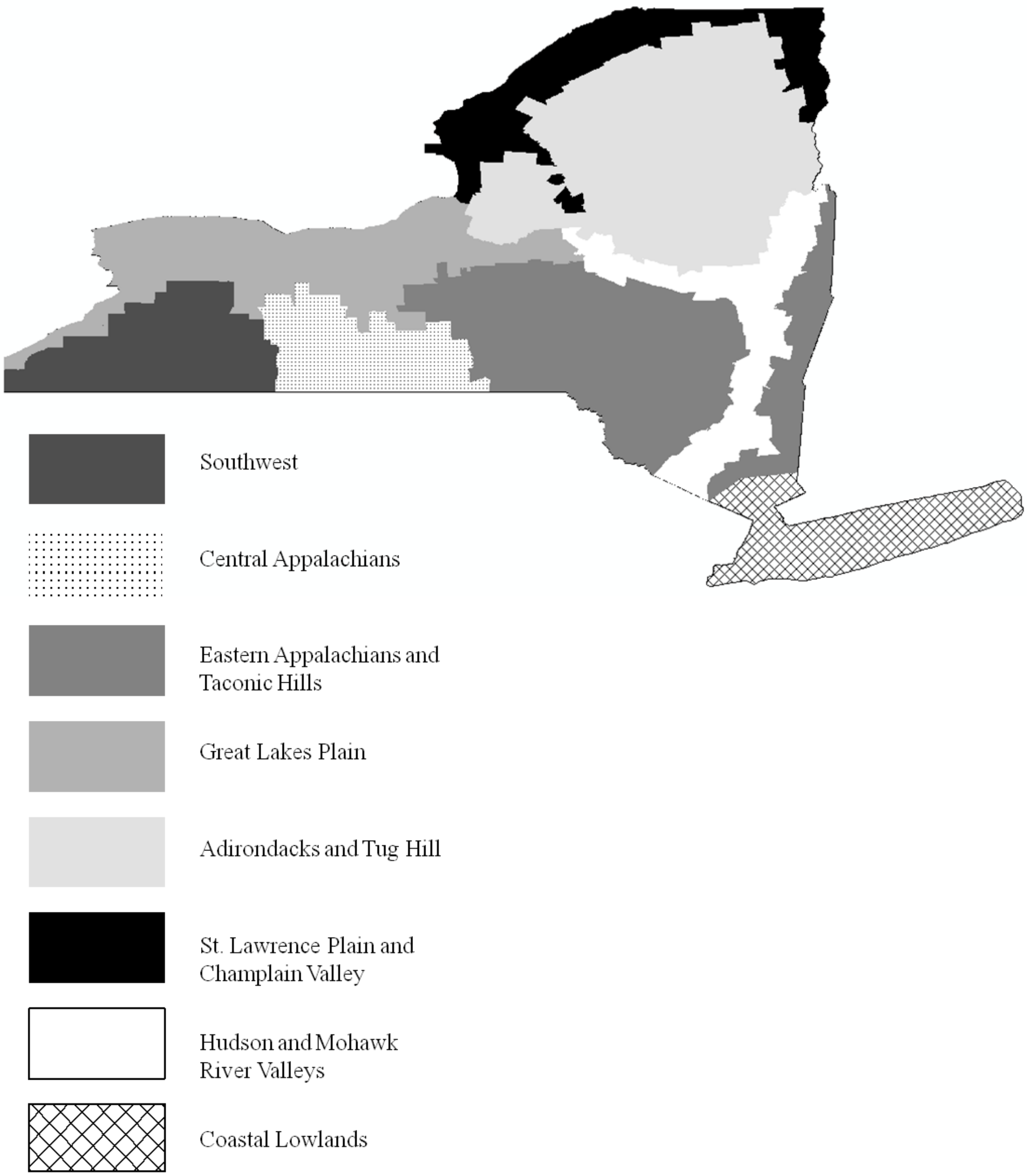

Figure 1-1. Climate-ecozones of New York State for studying the effects of weather and habitat on wild turkeys from 1984−2009.

METHODS

Data Acquisition

Harvest-effort data. – We used total birds harvested and reported each fall as the response variable, similar to the methods of Fleming and Porter (2007). New York State DEC requires that hunters report their take via mail, phone or internet. Fall reported harvest data are counts referenced to township (n = 918) and year (from 1984–2009).

Effort data were obtained from turkey hunter pressure surveys. NYS DEC sent surveys to 12,000 randomly-selected hunters after the fall harvest season had ended each year. In these surveys hunters indicated the number of days spent in the field hunting before they harvested a bird. The information was incorporated as the total number of days all hunters spent hunting in each township for each year (i.e., hunter days).

This study was exempt from filing an Institutional Animal Care and Use Committee Animal Use Form due to the use of historical data retrieved from NYS DEC, and we received an exemption letter from the committee.

Landscape-level habitat and weather data. – We obtained land-cover and land-use (LCLU) data for 1992 from the National Land Cover Database (NLCD), and for 1996, 2001, and 2006 from the Coastal Change Analysis Program (C-CAP) produced by the National Oceanic and Atmospheric Administration (NOAA) (Homer et al. 2004). C-CAP and NLCD are both satellite imagery of the earth's surface that have been classified into land-cover and land-use categories by cooperating U.S. federal agencies (i.e., NOAA and U.S. Geological Survey) before being provided to the general public for use. The spatial resolution (30 m^2) and extent were identical across the 4 data sets. The number and categorization of cover types were identical for the years 1996, 2001, and 2006. The study area included 3 different US Coast zones (63, 64, and

65; a C-CAP designation), and the data accuracy varied from 34% to 97% across zones, cover types, and years (U.S. Department of Commerce 2006a; b; c; d; 2007a; b; c; d; e). The NLCD from 1992 differed from the 3 C-CAP data sets in not including a grassland cover type, which was likely absorbed into one of the other 2 open types (i.e., pasture and hay and cultivated land). NLCD 1992 has 0% of the imagery classified as shrub.

We calculated landscape-level and class-level pattern metrics to evaluate land-cover composition and configuration of the NCLD and C-CAP LCLU data (Turner 1989, Yang and Liu 2005) in program Fragstats Version 3 (McGarigal et al. 2002, Marks et al. 2010) using townships as the landscape extents. Townships are valuable to use as landscape extents because we can measure aspects of the landscape that comprise habitat that support varying population levels. Townships are useful to identify detailed differences in population levels because populations fluctuate syncronously across townships that are within 150 km of each other (Fleming and Porter 2007b). Landscape-level metrics evaluate all the class-types that are found within a landscape extent while class-level metrics examine 6 individual ecologically important class-types to wild turkeys: cultivated land, pasture and hay, grassland, deciduous forest, evergreen forest, and mixed forest (Gefell 1991, Porter 1992, Glennon and Porter 1999). We excluded the shrubland class type from our class-level calculations because C-CAP only classified 3.3, 3.4, and 3.4% of the imagery as shrub in 1996, 2001, and 2006, respectively. We referenced the metrics for each township calculated from the NLCD 1992 data to the harvest data from years 1984–1992; the metrics calculated using C-CAP 1996 data were paired to the harvest data from years 1993–1996; the metrics calculated using C-CAP 2001 data were paired to the harvest data from years 1997–2001, and the metrics calculated using C-CAP 2006 data were paired to the harvest data from years 2002–2009.

We used composition and configuration metrics that represent important habitat to eastern wild turkeys. The 6 composition metrics were the proportions (PLAND) of class types: cultivated land, pasture and hay, grassland, deciduous forest, evergreen forest, and mixed forest. Our subset of configuration metrics from those used in past studies embodied the most descriptive metrics of landscape structure important for wild turkeys. The subset included metrics that quantified unrelated aspects of the landscape. We calculated contrast-weighted edge density (CWED) with the following weights: edges between forest types and open areas had the maximum weight of 1, while edges between any 2 other class types carried no weight (Glennon and Porter 1999, Fleming 2003). Thus, for our analyses CWED represented either the abrupt edges or the shrub transition between forests and open lands. We also calculated edge density (ED), interspersion and juxtaposition (IJI), mean shape index (MSI), patch area (AREA_MD), and the coefficient of variation of patch area (AREA_CV). Previous research has shown that high edge densities, high values of IJI, and high variation in forest patch sizes provide accessiblity to multiple cover types (Glennon and Porter 1999); accessibility is important for turkeys because they use multiple cover types for their different life history needs (Porter 1992). Complex-shaped patches of forest types (Fleming 2003) and large forest patch sizes (M. Schiavone, personal communication) have implications for accessibility of predators to turkey nests. Large patches of high shape complexity may hinder predators from finding nests.

We obtained raster data of total rainfall in the months of May and June for every year from Oregon State University's Parameter-elevation Regressions on Independent Slopes Model (PRISM) climate mapping system (PRISM Climate Group 2012). We calculated total May and June rainfall at the township scale by using the Zonal Statistics tool in ArcGIS 9.3 (ESRI 2011) averaging the raster values within each township.

Statistical Modeling

We sub-divided New York State into 7 commonly agreed-upon study areas for separate analyses. Our 7 areas were designed to combine the climate regions and the ecoregion delineations into areas alike in both climate and eco-geography (Fig 1-1) that we call climate-ecozones. We excluded the Coastal Lowlands climate-ecozone due to small sample size (*n* = 131). We used a spatial join in ArcGIS 9.3 to identify which townships occurred in each climate-ecozone. The Southwest had 111 townships, across 26 years (*n* = 2,748); the Central Appalachians had 77 townships, across 26 years (*n* = 1,832), and the Eastern Appalachians and Taconic Hills had 232 townships, across 26 years (*n* = 5,383). The Hudson and Mohawk River Valleys had 108 townships, across 26 years (*n* = 2,079), and the Great Lakes Plain had 177 townships, across 26 years (*n* = 1,976). The Adirondacks and Tug Hill had 120 townships, across 26 years (*n* = 1,073), and the St. Lawrence Plain and Champlain Valley had 67 townships, across 21 years (*n* = 745).

We used regression-based catch (i.e., harvest)-effort methods to model turkey harvest counts and assumed a linear relationship between harvest-effort (H/E) and abundance: H=qNE (Maunder and Punt 2004). For this model, q represents the catchability coefficient (i.e., the proportion of the population harvested per unit of hunting effort), E represents hunting effort (measured in hunter days), and N is the underlying population abundance for turkeys in a given township. In regression-based catch-effort models N and q are not separable without external information (Maunder and Punt 2004, Maunder et al. 2006), and thus our models predicted harvest as a function of covariates that capture heterogeneity in the product qN while accounting for hunting effort.

We fit mixed-effects regression models to harvest-effort and environmental covariate data to evaluate hypothesized drivers of fall harvest within each climate-ecozone with package glmmADMB version 0.7.7 (Skaug et al. 2013) in program R version 2.15.3 (R Development Core Team 2010). This package calls the random effects module in AD Model Builder (hereafter ADMB, http://admb-project.org, accessed December 2013; Fournier et al. 2012) to integrate out the random effects from the full likelihood and maximize the marginal likelihood function of the data (Bolker et al. 2013). We used the negative binomial distribution to fit generalized regression models because fall harvest count data were overdispersed (var > mean; Hilbe 2011). We expected turkey harvests from a given year to be more similar in adjacent townships, due to populations being correlated within 150 km (Fleming and Porter 2007b) and harvest within a given township to be similar from one year to the next, due to population size in one year being directly related to population size in the previous year, and due to other possible drivers not included as covariates. To accommodate this autocorrelation, we used a spatio-temporal random intercepts model to allow for random effects for township and year (Irwin et al. 2013). This effectively treated both township and year as block random effects (Bolker et al. 2013, Irwin et al. 2013). We used a random slope effect to allow strength of linear time trends in harvest-effort data to vary spatially among townships (Irwin et al. 2013). This effect was used because the range-wide general trend of wild turkey populations over the last 10 years was decreasing and the 20 years previous was increasing (Tapley et al. 2011) but the strength of population growth trends for individual townships may have varied (Fleming and Porter 2007b). We included the natural logarithm of effort as an offset to adjust the response variable scales in a manner analogous to common catch-effort analyses (Healy and Powell 1999, Maunder and Punt 2004) because hunting effort varied for each township-year. Furthermore, we used a natural log link to model the expected value of harvest counts as a function of hypothesized covariates:

$$\ln(\mu_{ij}) = \ln(\mathrm{effort}_{ij}) + \beta_0 + a_i + b_j + t_i\mathrm{Yr}_j + \Sigma^{Q}_{q=1}\beta_q X_{qij},$$

ensuring that the estimated mean values of harvest did not fall below 0. Here $effort_{ij}$ is the hunter days of effort at township i in year j, β_0 is the intercept, a_i is the random intercept for township i (constant across time), b_j is the random intercept for year j (constant across townships), t_i is the random slope for the linear time trend at township i, and β_q is the effect of covariate X_q on harvest, where Q is the total number of covariates (includes a fixed effect for year across all townships). The random intercepts and slope for all mixed-effects models were assumed to be independent and identically distributed normal random effects (e.g., a_i~N(0,σ^2_a); Irwin et al. 2013).

Because there are multiple ways to parameterize the variance-mean relationships for negative binomial regression, we used Akaike's Information Criterion (AIC; Burnham and Anderson 2002) to select the best model parameterization for each climate-ecozone. Each of the 4 models for each climate-ecozone was comprised of the global suite of fixed effects and one of the following 4 negative binomial error structures, including 2 zero-inflated: 1) quadratic relationship between variance and mean (μ) (Var(harvest) = $\mu(1 + \mu/\kappa)$); 2) linear relationship between variance and mean (Var(harvest) = $\phi\mu$; ϕ is a scaling parameter); 3) quadratic relationship between variance and mean with zero-inflation, and 4) linear relationship between variance and mean with zero-inflation.

After we allowed AIC to choose the best distribution structure for harvest counts we used the best error structure for each region to fit and compare fixed-effects models representing competing ecological hypotheses. We developed an a priori set of 74 models representing our ecological hypotheses. Each model had year as a fixed effect. Other models included different sets of environmental variables (Table 1-1). Landscape-level composition (LLCom) covariates were the proportions (_PLAND; between 0 and 1) and the quadratic term for each of the following class types: deciduous forest (DF), evergreen forest (EF), mixed forest (MF), grassland (GL), pasture and hay (PH), and cultivated land (CL). Landscape-level generalized composition (LLGCom) covariates were: total forested (F) and open (O) proportions, and the quadratic term for each. Landscape-level configuration (LLCon) covariates were: ED, CWED, and IJI, and the quadratic term for each. Quadratic terms were investigated because we anticipated that increasing proportions of cover types were beneficial up to a certain level above which the landscape was considered too homogeneous to be good habitat. Additionally, increasing levels of fragmentation, represented by the configuration covariates, likely were beneficial up to a certain level above which the landscape was considered too fragmented to be good habitat. Class-level configuration (CLCon) covariates were: the median patch area (_ AREA_MD), the variation in patch sizes (_ AREA_CV), and the mean shape index (_MSI) for each of the 3 forest types, as well as the CWED for evergreen and mixed forests. Weather covariates were total May and June rainfall: MR and JR. The interactions included the main effects of either MR or JR and one of the landscape-level composition covariates (LLCom), one of the landscape-level generalized composition covariates (LLGCom), one of the landscape-level configuration covariates (LLCon), and one of the class-level configuration covariates (CLCon). The covariates were all standardized by subtracting the mean from each data point and dividing by the standard deviation. We calculated Pearson's product-moment correlation coefficients to evaluate multicolinearity between pairs of landscape pattern metric covariates and between pairs of weather covariates in program R 2.15.3 (R Development Core Team 2010). Because evidence suggests pairwise correlations of regression covariates does not substantially affect standard error estimates until correlations are strong (approx. > 0.8; Fox 2008), we used a $r > 0.7$ as a conservative threshold for including correlated covariates together in a regression model. Thus, if a priori models included a pair of correlated covariates we subsequently removed one of the correlated covariates prior to model fitting. We removed the class-level covariate if it was correlated with a landscape-level covariate. If two different forest class-level covariates were correlated we excluded evergreen over mixed or deciduous; we excluded mixed over deciduous, because deciduous and mixed forests provide more food than evergreen and deciduous is misclassified at a lower rate than mixed. If two different configuration covariates of the same forest type were correlated, the more difficult of the two to interpret was removed (e.g., the CV of mixed forest patch areas was excluded from a model if it was correlated with proportion of mixed forest).

Table 1-1. Model set for analysis of drivers of fall harvest of wild turkeys in New York during 1984-2009 in each of 7 climate-ecozones. Models below are for fixed effects only. The random effects were the same across all models within the set.

Model
Y [a]
Y + LLCon [b] + $LLCon^2$ [c]
Y + LLCon
Y + LLCom [d] + $LLCom^2$ [e] + LLCon + $LLCon^2$ + CLCon [f]
Y + LLCom + LLCon + CLCon
Y + LLGCom [g] + $LLGCom^2$ [h] + LLCon + $LLCon^2$ + CLCon
Y + LLGCom + LLCon + CLCon
Y + LLCom + $LLCom^2$
Y + LLCom
Y + LLGCom + $LLGCom^2$
Y + LLGCom
Y + MR [i]
Y + MR + LLCon + $LLCon^2$
Y + MR + LLCon
Y + MR + LLCon + $LLCon^2$ + (MR × LLCon)
Y + MR + LLCon + (MR × LLCon)
Y + MR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon
Y + MR + LLCom + LLCon + CLCon

Table 1-1 (cont'd)

Y + MR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon

Y + MR + LLGCom + LLCon + CLCon

Y + MR + LLCom + $LLCom^2$

Y + MR + LLCom

Y + MR + LLGCom + $LLGCom^2$

Y + MR + LLGCom

Y + MR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLCon) + (MR × CLCon)

Y + MR + LLCom + LLCon + CLCon + (MR × LLCon) + (MR × CLCon)

Y + MR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon)

Y + MR + LLGCom + LLCon + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon)

Y + MR + LLCom + $LLCom^2$ + (MR × LLCom)

Y + MR + LLCom + (MR × LLCom)

Y + MR + LLGCom + $LLGCom^2$ + (MR × LLGCom)

Y + MR + LLGCom + (MR × LLGCom)

Y + JR [j]

Y + JR + LLCon + $LLCon^2$

Y + JR + LLCon

Y + JR + LLCon + $LLCon^2$ + (JR × LLCon)

Y + JR + LLCon + (JR × LLCon)

Y + JR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon

Table 1-1 (cont'd)

Y + JR + LLCom + LLCon + CLCon

Y + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon

Y + JR + LLGCom + LLCon + CLCon

Y + JR + LLCom + LLCom^2

Y + JR + LLCom

Y + JR + LLGCom + LLGCom^2

Y + JR + LLGCom

Y + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (JR × LLCon) + (JR × CLCon)

Y + JR + LLCom + LLCon + CLCon + (JR × LLCon) + (JR × CLCon)

Y + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)

Y + JR + LLGCom + LLCon + CLCon + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)

Y + JR + LLCom + LLCom^2 + (JR × LLCom)

Y + JR + LLCom + (JR × LLCom)

Y + JR + LLGCom + LLGCom^2 + (JR × LLGCom)

Y + JR + LLGCom + (JR × LLGCom)

Y + MR + JR

Y + MR + JR + LLCon + LLCon^2

Y + MR + JR + LLCon

Y + MR + JR + LLCon + LLCon^2 + (MR × LLCon)

Y + MR + JR + LLCon + (MR × LLCon) + (JR × LLCon)

Y + MR + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon

Table 1-1 (cont'd)

Y + MR + JR + LLCom + LLCon + CLCon
Y + MR + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon
Y + MR + JR + LLGCom + LLCon + CLCon
Y + MR + JR + LLCom + $LLCom^2$
Y + MR + JR + LLCom
Y + MR + JR + LLGCom + $LLGCom^2$
Y + MR + JR + LLGCom
Y + MR + JR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLCon) + (MR × CLCon) + (JR × LLCon) + (JR × CLCon)
Y + MR + JR + LLCom + LLCon + CLCon + (MR × LLCon) + (MR × CLCon) + (JR × LLCon) + (JR × CLCon)
Y + MR + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)
Y + MR + JR + LLGCom + LLCon + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)
Y + MR + JR + LLCom + $LLCom^2$ + (MR × LLCom) + (JR × LLCom)
Y + MR + JR + LLCom + (MR × LLCom) + (JR × LLCom)
Y + MR + JR + LLGCom + $LLGCom^2$ + (MR × LLGCom) + (JR × LLGCom)
Y + MR + JR + LLGCom + (MR × LLGCom) + (JR × LLGCom)

Y [a]: Yr

LLCon [b]: Landscape-level Configuration: edge density(ED), contrast-weighted (CW)ED, and interspersion and juxtaposition (IJI)

$LLCon^2$ [c]: Landscape-level $Configuration^2$: ED^2, $CWED^2$, and IJI^2

Table 1-1 (cont’d)

LLCom [d]:	Landscape-level Composition: deciduous forest (DF)_ proportion (PLAND), evergreen forest (EF)_PLAND, mixed forest (MF)_PLAND, grassland (GL)_PLAND, pasture and hay (PH)_PLAND, and cultivated land (CL)_PLAND
$LLCom^2$ [e]:	Landscape-level $Composition^2$: DF_PLAND^2, EF_PLAND^2, MF_PLAND^2, GL_PLAND^2, PH_PLAND^2, and CL_PLAND^2
CLCon [f]:	Class-level Configuration: DF_ median patch area (AREA_MD), DF_ CV of patch areas (AREA_CV), DF_ mean shape index (MSI), EF_ AREA_MD, EF_ AREA_CV, EF_ MSI, EF_ CWED, MF_ AREA_MD, MF_ AREA_CV, MF_ MSI, and MF_ CWED
LLGCom [g]:	Landscape-level Generalized Composition: forested (F)_PLAND and open (O)_PLAND
$LLGCom^2$ [h]:	Landscape-level Generalized $Composition^2$: F_PLAND^2 and O_PLAND^2
MR [i]:	May Rainfall
JR [j]:	June Rainfall

We reported on the most parsimonious model (smallest AIC) from each climate-ecozone. When the 95% confidence intervals of the coefficient estimates did not overlap 0, the relationships between ecological variables and harvest were considered statistically significant.

To evaluate model assumptions and fit we used Anscombe residuals for diagnostic plots and calculated root mean squared-error (RMSE; i.e., square-root of average squared differences between fitted and observed harvest counts).

RESULTS

The negative binomial error structure whose variance increases linearly (i.e., Var(harvest) = $\phi\mu$; Table 1-2) was selected for 2 (i.e., the Southwest and Central Appalachians) of the 7 climate-ecozones evaluated. The negative binomial error structure with a quadratic relationship between the variance and mean (i.e., Var(harvest)= $\mu(1 + \mu/\kappa)$ was selected for all other regions (Table 1-2). The difference of AIC scores between the best and second best negative binomial error structures were ≥ 2 for all regions.

Table 1-2. Model set for analysis of error structures in New York during 1984-2009 in each of 7 climate-ecozones. Models below included all the random effects and the largest set of covariates. The random effects were spatially and temporally varying intercepts, and temporally-varying slopes.

	Climate-Ecozone													
	Southwest		Central Appalachians		Eastern Appalachians and Taconic Hills		Hudson and Mohawk River Valleys		Great Lakes Plain		Adirondacks and Tug Hill		St. Lawrence Plain and Champlain Valley	
Error structure	ΔAIC	K	ΔAIC	K	ΔAIC	K	ΔAIC	K	ΔAIC	K	ΔAIC	K	ΔAIC	K
quadratic[a]	138.9	68	91.7	68	0	68	0	68	0	68	0	68	0	68
quadratic with zero inflation	132.1	69	93.6	69	-[c]	-	2	69	2	69	2	69	2	69
linear[b]	0	68	0	68	113.2	68	31.1	68	-	-	96.5	68	58.8	68
linear with zero inflation	2	69	2	69	2603	69	30.9	69	-	-	90.2	69	-	-

[a] Var(harvest) = μ(1+ μ/κ)

[b] Var(harvest) = ϕμ

[c] Model failed to converge

Ecological Variables

Southwest. – The top model was Y + JR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon (Table 1-3). The second to the top model, Y + MR + JR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon, was within 2 AIC, but the additional covariate (May rainfall) was not statistically significant. Coefficient estimates from the top model indicated the following all were negatively associated with fall turkey harvest: total June rainfall ($\beta = -0.077$, 95% CI = −0.136 to −0.019, $P = 0.009$; Fig 1-2A), the proportion of the township covered by mixed forest ($\beta = -0.314$, 95% CI = −0.546 to −0.082, $P = 0.008$), and median area of mixed forest patches ($\beta = -0.102$, 95% CI = −0.164 to −0.041, $P = 0.001$). Evergreen forest cover had varied relationships with fall turkey harvest. Proportion of a township covered by evergreen forest was quadratically related to harvest ($\beta = 0.235$, 95% CI = 0.089 to 0.382, $P = 0.002$, $\beta^2 = -0.056$, 95% CI = −0.093 to −0.019, $P = 0.003$). However, examining evergreen forest patches reveals that the increasing median area of evergreen forest patches ($\beta = -0.072$, 95% CI = −0.122 to −0.022, $P = 0.005$) was negatively related to harvest, while the more variation in evergreen forest patch area (measured using CV) within a township was positively associated with fall turkey harvest ($\beta = 0.055$, 95% CI = 0.005 to 0.105, $P = 0.03$). Conversely, the increasing variation in the area of deciduous forest patches was negatively related to harvest ($\beta = -0.078$, 95% CI = −0.142 to −0.013, $P = 0.019$). There was a quadratic relationship between landscape-level edge density and harvest ($\beta = -0.019$ 95% CI = −0.14 to 0.101, $P = 0.752$, $\beta^2 = -0.047$, 95% CI = −0.09 to −0.004, $P = 0.033$), although the linear term was not significantly different than zero. The root mean square error (RMSE) = 7.447; this value is low compared to the RMSE of the mean model (i.e., 11.598) and therefore the model fits the observed harvest data well: within 7–8 birds.

Table 1-3. Partial model sets for the ecological structures in New York during 1984-2009 in each of 7 climate-ecozones. Each of the models included all the random effects and the error structure previously chosen by AIC. Only models within 2 AIC of the top are included, or the top 2 models are included if the second is not within 2 AIC. K is the number of parameters.

Climate-Ecozone	Model name	ΔAIC	K
Southwest: Cattaraugus Highlands and Allegany Hills	Y [a] + JR [b] + LLCom [c] + $LLCom^2$ [d] + LLCon [e] + $LLCon^2$ [f] + CLCon [g]	0	34
	Y + MR [h] + JR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon	1.5	35
Central Appalachians	Y + MR + LLGCom [i] + $LLGCom^2$ [j] + LLCon + $LLCon^2$ + CLCon	0	27
	Y + MR + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon	0.4	28
Eastern Appalachians and Taconic Hills	Y + MR + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	0	48
	Y + MR + JR + LLCom + $LLCom^2$ + (MR × LLCom) + (JR × LLCom)	12	32
Hudson and Mohawk River Valleys	Y + MR + JR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon	0	35
	Y + MR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon	1	34
Great Lakes Plain	Y + MR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon	0	25
	Y + MR + LLGCom	0.2	20
	Y + MR + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon	1.9	26

Table 1-3 (cont'd)

Adirondacks and Tug Hill	Y + JR + LLCon + $LLCon^2$ + (JR × LLCon)	0	16
	Y + JR + LLCon + (JR × LLCon)	0	13
St. Lawrence Plain and Champlain Valley	Y + LLCom + $LLCom^2$	0	18
	Y + MR + LLCom + $LLCom^2$	1.9	19
	Y + JR + LLCom + $LLCom^2$	2	19

Y [a]: Yr

JR [b]: June Rainfall

LLCom [c]: Landscape-level Composition: deciduous forest (DF)_ proportion (PLAND), evergreen forest (EF)_PLAND, mixed forest (MF)_PLAND, grassland (GL)_PLAND, pasture and hay (PH)_PLAND, and cultivated land (CL)_PLAND

$LLCom^2$ [d]: Landscape-level $Composition^2$: DF_PLAND^2, EF_PLAND^2, MF_PLAND^2, GL_PLAND^2, PH_PLAND^2, and CL_PLAND^2

LLCon [e]: Landscape-level Configuration: edge density(ED), contrast-weighted (CW)ED, and interspersion and juxtaposition (IJI)

$LLCon^2$ [f]: Landscape-level $Configuration^2$: ED^2, $CWED^2$, and IJI^2

CLCon [g]: Class-level Configuration: DF_ median patch area (AREA_MD), DF_ CV of patch areas (AREA_CV), DF_ mean shape index (MSI), EF_ AREA_MD, EF_ AREA_CV, EF_ MSI, EF_ CWED, MF_ AREA_MD, MF_ AREA_CV, MF_ MSI, and MF_ CWED

MR [h]: May Rainfall

LLGCom [i]: Landscape-level Generalized Composition: forested (F)_PLAND and open (O)_PLAND

Table 1-3 (cont'd)

$LLGCom^{2}$ [j]: Landscape-level Generalized Composition^2: F_PLAND^2 and O_PLAND^2

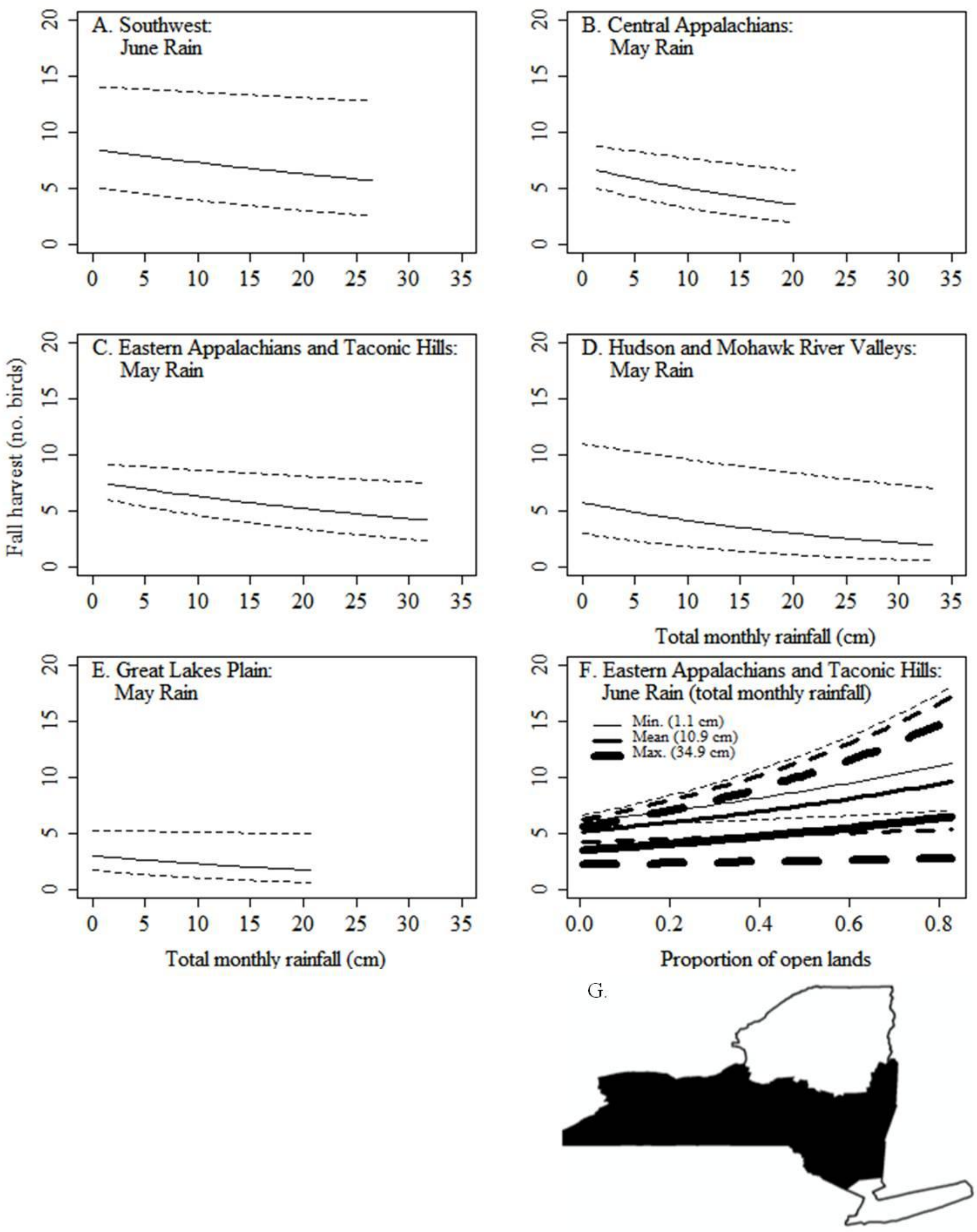

Figure 1-2. Spring rainfall effects on township-level fall wild turkey harvest (adjusted by effort) across several climate-ecozones in New York State (G) from 1984−2009 (95% confidence

Figure 1-2 (cont'd)

intervals indicated by dashed lines). In the Southwest June rainfall was negatively associated with fall harvest (A), while in the Central Appalachians (B), the Eastern Appalachians and Taconic Hills (C), the Hudson and Mohawk River Valleys (D), and the Great Lakes Plain (E) May rainfall was negatively associated with fall harvest. In the Eastern Appalachians and Taconic Hills (F), there was a significant interaction between June rainfall and proportion of open lands.

Central Appalachians. – The top model was Y + MR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon (Table 1-3). The second to the top model, Y + MR + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon, was within 2 AIC, but the additional covariate (June rainfall) was not statistically significant. Coefficient estimates from the top model indicated that the following were negatively associated with fall harvest: May rainfall ($\beta = -0.145$, 95% CI = −0.223 to −0.067, $P < 0.001$; Fig 1-2B) and landscape-level edge density ($\beta = -0.12$, 95% CI = −0.225 to −0.016, $P = 0.024$). There was a u-shaped quadratic relationship between landscape-level contrast-weighted edge density and harvest ($\beta = -0.315$, 95% CI = −0.452 to −0.178, $P < 0.001$, $\beta^2 = 0.16$, 95% CI = 0.104 to 0.267, $P < 0.001$; Fig 1-3A), implying the lowest harvest were located in townships with intermediate values for this variable. There was a hump-shaped relationship between proportion of a township covered by forested lands and harvest ($\beta = 0.089$, 95% CI = −0.067 to 0.245, $P = 0.262$, $\beta^2 = -0.193$, 95% CI = −0.269 to −0.116, $P < 0.001$), although the linear term was not significantly different than zero. Finally, the following were positively related to harvest: increasing contrast-weighted edge density of evergreen forest (edges only between evergreen forest patches and any other cover type; $\beta = 0.126$, 95% CI = 0.0434 to 0.209, $P = 0.003$; Fig 1-3B), proportion of a township covered by open lands ($\beta = 0.257$, 95% CI = 0.095 to 0.419, $P = 0.002$), and median area of deciduous forest patches ($\beta = 0.136$, 95% CI = 0.066 to 0.206, $P < 0.001$). The RMSE = 5.571; this value is low compared to the RMSE of the mean model (i.e., 8.075) and therefore the model fits the observed harvest data well: within 5–6 birds.

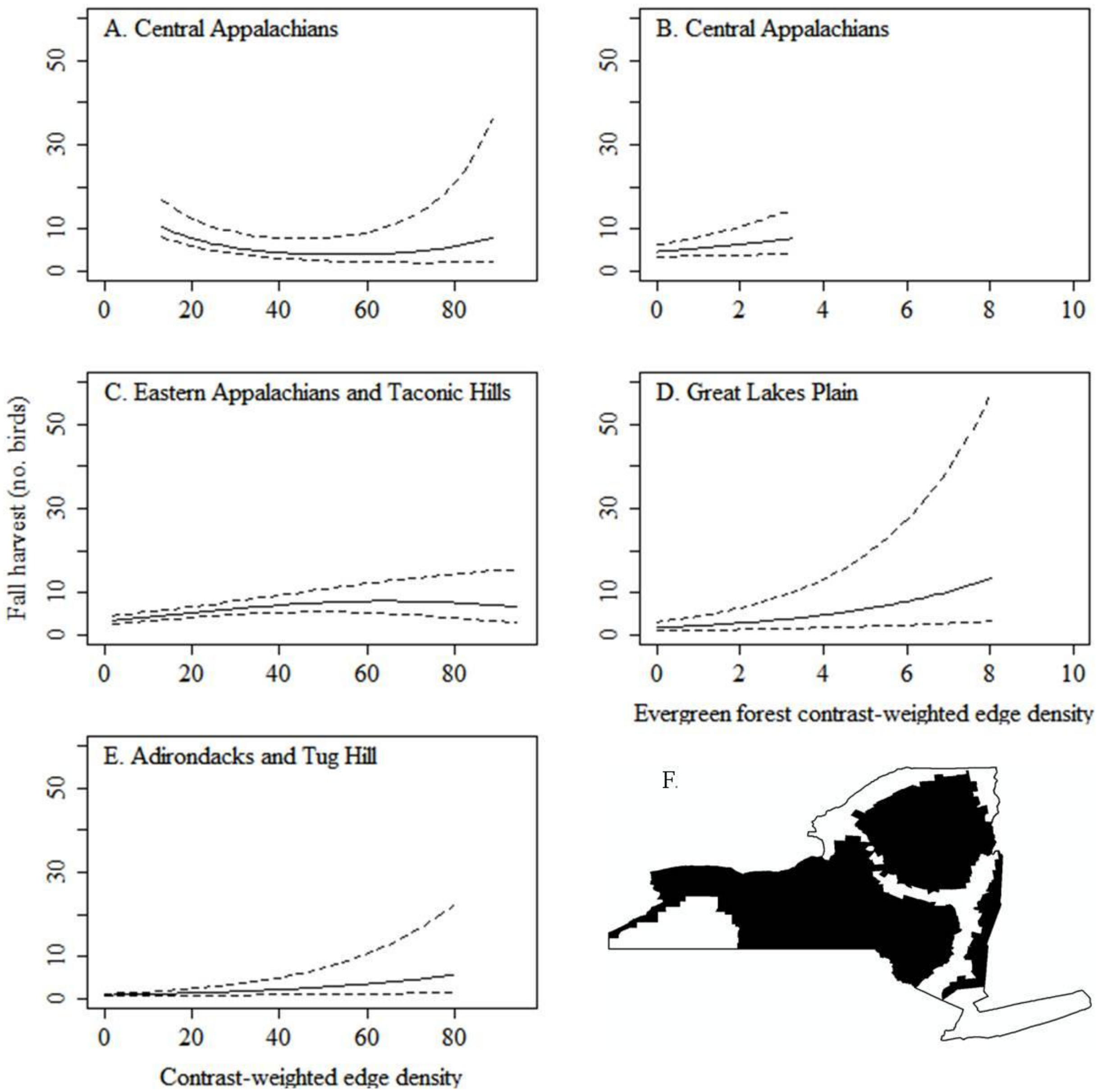

Figure 1-3. Contrast-weighted edge density (CWED) effects on township-level fall wild turkey harvest (adjusted by effort) across several climate-ecozones in New York State (F) from 1984−2009 (95% confidence intervals indicated by dashed lines). Low values and high values of landscape-level CWED increased fall harvest, while intermediate values decreased fall harvest in the Central Appalachians (A). Conversely, intermediate values increased fall harvest in the Eastern Appalachians and Taconic Hills (C). In the Central Appalachians (B) and the Great

Figure 1-3 (cont'd)

Lakes Plain (D), evergreen forest CWED increased fall harvest. In the Adirondacks and Tug Hill (E) landscape-level CWED increased fall harvest.

Eastern Appalachians and Taconic Hills. – The top model was Y + MR + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon) (Table 1-3). The coefficient estimates from the top model indicated that the following were negatively related to harvest: total May rainfall ($\beta = -0.094$, 95% CI = −0.156 to −0.033, $P = 0.003$; Fig 1-2C), June rainfall ($\beta = -0.087$, 95% CI = −0.148 to −0.027, $P = 0.005$), and the increasing mean shape index of evergreen forest patches ($\beta = -0.081$, 95% CI = −0.157 to −0.004, $P = 0.04$). Conversely, increasing median area of evergreen forest patches ($\beta = 0.083$, 95% CI = 0.022 to 0.144, $P = 0.008$) was positively associated with harvest, and harvest increased through time over the study period ($\beta = 0.109$, 95% CI = 0.083 to 0.135, $P < 0.001$). Additionally, there was a quadratic relationship between landscape-level edge density ($\beta = 0.005$, 95% CI = −0.05 to 0.06, $P = 0.862$, $\beta^2 = 0.036$, 95% CI = 0.003 to 0.068, $P = 0.034$; the linear term was not significantly different than zero) and harvest, and hump-shaped quadratic relationships between the following and harvest: landscape-level contrast-weighted edge density ($\beta = 0.225$, 95% CI = 0.156 to 0.295, $P < 0.001$, $\beta^2 = -0.078$, 95% CI = −0.118 to −0.038, $P < 0.001$; Fig 1-3C) and proportion of open lands within a township ($\beta = 0.12$, 95% CI = 0.045 to 0.194, $P = 0.002$, $\beta^2 = -0.05$, 95% CI = −0.094 to −0.007, $P = 0.024$).

There were 4 significant interactions, all of which the main effect of total rainfall (May or June) in the interaction was significant, but only one of which the other main effect (proportion of open lands) was significant (see above). There was a positive relationship between the interaction of total May rainfall and landscape-level interspersion and juxtaposition and harvest ($\beta = 0.078$, 95% CI = 0.031 to 0.119, $P < 0.001$). There was a negative relationship between the interaction of total May rainfall and evergreen forest contrast-weighted edge density and harvest

(β = −0.051, 95% CI = −0.086 to −0.015, P = 0.005). There was a negative relationship between the interaction of total June rainfall and landscape-level interspersion and juxtaposition and harvest (β = −0.046, 95% CI = −0.089 to −0.004, P = 0.034). There was a positive relationship between the interaction of total June rainfall and proportion of open lands and harvest (β = 0.059, 95% CI = 0.016 to 0.103, P = 0.007; Fig 1-2F). The RMSE = 9.365; this value is low compared to the RMSE of the mean model (i.e., 17.884) and therefore the model fits the observed harvest data well: within 9–10 birds.

Hudson and Mohawk River Valleys. – The top model was Y + MR + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon (Table 1-3). The second to the top model, Y + MR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon, was within 2 AIC, but had one fewer covariate. The coefficient estimates from the top model indicated that total May rainfall (β = −0.162, 95% CI = −0.256 to −0.067, P < 0.001; Fig 1-2D) was negatively related to harvest. The following were positively associated with harvest: proportions of a township covered by pasture and hay (β = 0.469, 95% CI = 0.257 to 0.681, P < 0.001) and deciduous forest (β = 0.18, 95% CI = 0.01 to 0.351, P = 0.038), while harvest increased through time over the study period (β = 0.083, 95% CI = 0.051 to 0.115, P < 0.001). Mixed forest cover had varied relationships with fall turkey harvest. Proportion of a township covered by mixed forest (β = 0.43, 95% CI = 0.218 to 0.641, P < 0.001) was positively related to harvest, while the following were negatively related to harvest: mean shape index of mixed forest patches (β = −0.146, 95% CI = −0.254 to −0.038, P = 0.008), and the contrast-weighted edge density of mixed forest (edges only between mixed forest patches and any other cover type; β = −0.214, 95% CI = −0.399 to −0.03, P = 0.023). The following were negatively related to harvest: increasing median area of deciduous forest patches (β = −0.137, 95% CI = −0.227 to −0.046, P = 0.003) and the proportion of townships covered in grasslands (β = −0.228, 95% CI = −0.442 to −0.015, P = 0.036). There was a u-shaped quadratic relationship between proportion of townships covered in evergreen forest and harvest (β = −0.265, 95% CI = −0.496 to −0.033, P = 0.025, β^2 = 0.135, 95% CI = 0.0697 to 0.2, P < 0.001). The RMSE = 8.619; this value is low compared to the RMSE of the mean model (i.e., 11.434) and therefore the model fits the observed harvest data well: within 8–9 birds.

Great Lakes Plain. – The top model was Y + MR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon (Table 1-3). The second to the top model, Y + MR + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon, was within 2 AIC, but the June rainfall covariate was not statistically significant. The coefficient estimates indicated that the following were negatively associated with harvest: total May rainfall (β = −0.117, 95% CI = −0.22 to −0.014, P = 0.026; Fig 1-2E) and mean shape index of mixed forest patches (β = −0.175, 95% CI = −0.293 to −0.057, P = 0.004). Conversely, the following were positively associated with harvest: landscape-level interspersion and juxtaposition (β = 0.193, 95% CI = 0.011 to 0.375, P = 0.038; Fig 1-4A), contrast-weighted edge density of evergreen forest (β = 0.314, 95% CI = 0.191 to 0.438, P < 0.001; Fig 1-3D), and median area of deciduous forest patches (β = 0.179, 95% CI = 0.062 to 0.297, P = 0.003). Lastly, there was a u-shaped quadratic relationship between landscape-level contrast-weighted edge density (β = −0.146, 95% CI = −0.366 to 0.075, P = 0.2, β^2 = 0.085, 95% CI = 0.01 to 0.16, P = 0.027; the linear term was not significantly different than zero) and harvest. The RMSE = 4.694; this value is low compared to the RMSE of the mean model (i.e., 6.223) and therefore the model fits the observed harvest data well: within 4–5 birds.

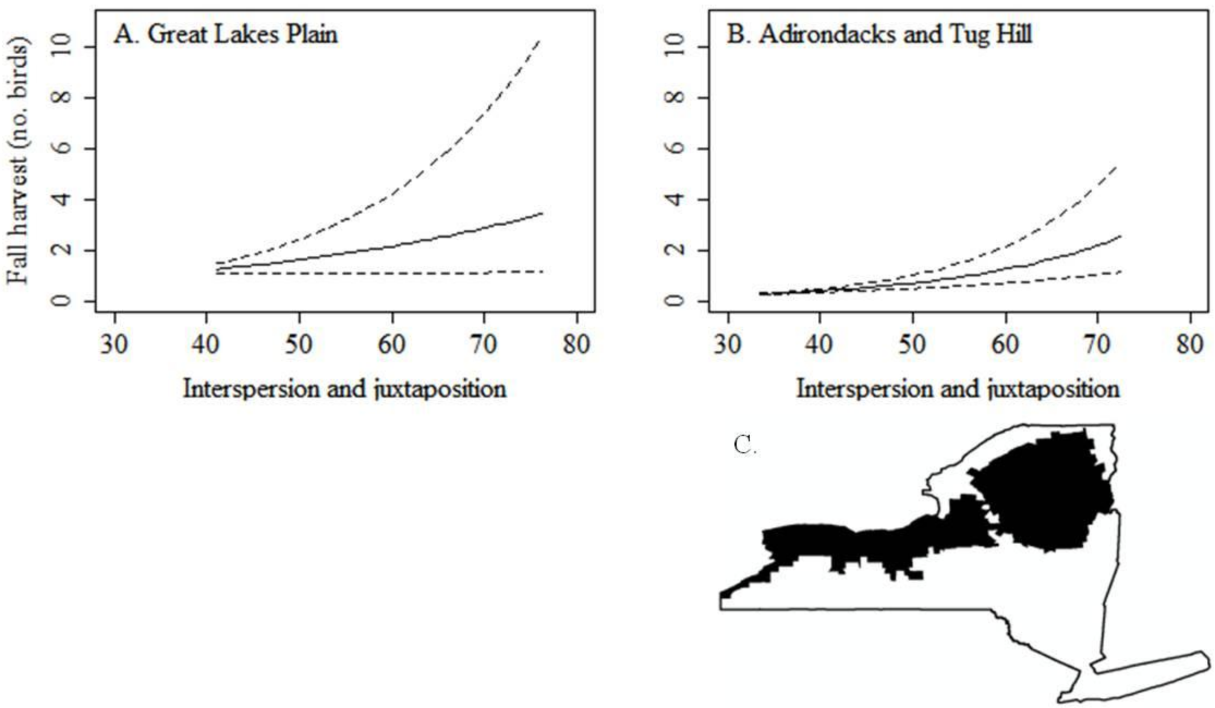

Figure 1-4. Interspersion and juxtaposition (IJI) effects on township-level fall wild turkey harvest (adjusted by effort) across several climate-ecozones in New York State (C) from 1984−2009 (95% confidence intervals indicated by dashed lines). In the agricultural Great Lakes Plain (A) and in the heavily forested landscape of the Adirondacks and Tug Hill, as IJI increased fall harvest increased.

Adirondacks and Tug Hill. – The top model was Y + JR + LLCon + (JR × LLCon) (Table 1-3). The second to the top model, Y + JR + LLCon + $LLCon^2$ + (JR × LLCon), was within 2 AIC, but the 3 additional covariates were not statistically significant. The modeling indicated that the following were positively related to harvest: landscape-level contrast-weighted edge density (β = 0.322, 95% CI = 0.145 to 0.499, P < 0.001; Fig 1-3E), and interspersion and juxtaposition (β = 0.49, 95% CI = 0.327 to 0.653, P < 0.001; Fig 1-4B), and mean harvest increased through time (β = 0.053, 95% CI = 0.002 to 0.104, P = 0.04). However, interspersion and juxtaposition also interacted with June rainfall (β = 0.156, 95% CI = 0.035 to 0.278, P = 0.012) to influence harvest. The RMSE = 4.583; this value is low and similar to the RMSE of the mean model (i.e., 4.338) and therefore the model fits the observed harvest data well: within 4–5 birds.

St. Lawrence Plain and Champlain Valley. – The top model was Y + LLCom + $LLCom^2$ (Table 1-3). The second to the top model, Y + MR + LLCom + $LLCom^2$, was within 2 AIC, but May rainfall was not statistically significant. The analysis indicated that there was a quadratic relationship between proportion of mixed forest within a township and harvest (β = −0.834, 95% CI = −1.255 to −0.413, P < 0.001, β^2 = 0.18, 95% CI = 0.014 to 0.346, P = 0.034), suggesting that the lowest mean harvests were expected at the intermediate values of mixed forest coverage. There was a u-shaped quadratic relationship between proportion of grassland (β = −0.155, 95% CI = −0.396 to 0.085, P = 0.206, β^2 = 0.085, 95% CI = 0.009 to 0.162, P = 0.03) and harvest, although the linear term was not significantly different than zero. The RMSE = 4.92; this value is low compared to the RMSE of the mean model (i.e., 5.277) and therefore the model fits the observed harvest data well: within 4–5 birds.

Each climate-ecozone had a different top model and therefore a different set of drivers affecting fall harvest. However, there was some overlap in the drivers of fall harvest among the climate-ecozones (Table 1-4).

Table 1-4. Directional effects of covariate from the top models in each of 7 climate-ecozones in New York during 1984−2009. The symbols are as follows: +, -, or 0 for each variable (indicating a positive coefficient, a negative coefficient, or zero for variables not included in any of the top AIC models, respectively). The gray shaded symbols indicate a coefficient whose 95% confidences intervals did not overlap 0.

		Climate-ecozone						
		South west	Central Appal-achians	Eastern Appal-achians and Taconic Hills	Hudson and Mo-hawk River Valleys	Great Lakes Plain	Adiron-dacks and Tug Hill	St. Lawrence Plain and Champlain Valley
Functional Group	Covariate	Direction of Effect						
	Intercept	-	-	-	-	-	-	-
Y [a]	Yr	-	+	+	+	-	+	+
MR [b]	MR	0	-	-	-	-	0	0
JR [c]	JR	-	0	-	+	0	-	0
LLCon [d]	ED	-	-	+	+	-	-	0
	CWED	+	-	+	-	-	+	0
	IJI	+	+	-	+	+	+	0
$LLCon^2$ [e]	ED^2	-	-	+	-	-	0	0
	$CWED^2$	+	+	-	+	+	0	0
	IJI^2	+	+	+	-	-	0	0

Table 1-4 (cont'd)

LLGCom[f] + LLGCom^2 [g]	O _PLAND	0	+	+	0	-	0	0
	O _PLAND^2	0	+	-	0	-	0	0
	F _PLAND	0	+	0	0	+	0	0
	F _PLAND^2	0	-	0	0	+	0	0
LLCom [h] + LLCom^2 [i]	CL _PLAND	-	0	0	+	0	0	-
	CL _PLAND^2	-	0	0	+	0	0	+
	PH _PLAND	-	0	0	+	0	0	+
	PH _PLAND^2	-	0	0	-	0	0	-
	GL _PLAND	+	0	0	-	0	0	-
	GL _PLAND^2	-	0	0	+	0	0	+
	DF _PLAND	-	0	0	+	0	0	+
	DF _PLAND^2	-	0	0	+	0	0	-
	EF _PLAND	+	0	0	-	0	0	-
	EF _PLAND^2	-	0	0	+	0	0	+
	MF _PLAND	-	0	0	+	0	0	-
	MF _PLAND^2	+	0	0	-	0	0	+

Table 1-4 (cont’d)

CLCon [j]	DF _MSI	+	+	+	-	+	0	0
	EF _CWED	+	+	-	+	+	0	0
	EF _MSI	-	-	-	+	+	0	0
	MF _CWED	0	-	0	-	0	0	0
	MF _MSI	-	+	-	-	-	0	0
	DF_AREA _MD	+	+	-	-	+	0	0
	DF_AREA _CV	-	+	-	-	-	0	0
	EF_AREA _MD	-	+	+	+	+	0	0
	EF_AREA _CV	+	+	+	-	0	0	0
	MF_AREA _MD	-	+	0	0	+	0	0
MR × LLCon	MR × ED	0	0	+	0	0	0	0
	MR × CWED	0	0	-	0	0	0	0
	MR × IJI	0	0	+	0	0	0	0
MR × LLGCom	MR × O_PLAND	0	0	-	0	0	0	0

Table 1-4 (cont'd)

MR × CLCon	MR × DF_MSI	0	0	-	0	0	0	0
	MR × EF_CWED	0	0	-	0	0	0	0
	MR × EF_MSI	0	0	+	0	0	0	0
	MR × MF_MSI	0	0	-	0	0	0	0
	MR × DF_AREA_MD	0	0	+	0	0	0	0
	MR × DF_AREA_CV	0	0	+	0	0	0	0
	MR × EF_AREA_MD	0	0	+	0	0	0	0
	MR × EF_AREA_CV	0	0	+	0	0	0	0
JR × LLCon	JR × ED	0	0	+	0	0	+	0
	JR × CWED	0	0	-	0	0	+	0
	JR × IJI	0	0	-	0	0	+	0
JR × LLGCom	JR × O_PLAND	0	0	+	0	0	0	0

Table 1-4 (cont'd)

	JR × DF_MSI	0	0	+	0	0	0	0
	JR × EF_CWED	0	0	+	0	0	0	0
	JR × EF_MSI	0	0	-	0	0	0	0
	JR × MF_MSI	0	0	+	0	0	0	0
JR × CLCon	JR × DF_AREA_MD	0	0	-	0	0	0	0
	JR × DF_AREA_CV	0	0	-	0	0	0	0
	JR × EF_AREA_MD	0	0	-	0	0	0	0
	JR × EF_AREA_CV	0	0	-	0	0	0	0

Y [a]: Yr

MR [b]: May Rainfall

JR [c]: June Rainfall

LLCon [d]: Landscape-level Configuration: edge density(ED), contrast-weighted (CW)ED, and interspersion and juxtaposition (IJI)

$LLCon^2$ [e]: Landscape-level $Configuration^2$: ED^2, $CWED^2$, and IJI^2

LLGCom [f]: Landscape-level Generalized Composition: forested (F)_PLAND and open (O)_PLAND

$LLGCom^2$ [g]: Landscape-level Generalized $Composition^2$: F_PLAND^2 and O_PLAND^2

LLCom [h]: Landscape-level Composition: deciduous forest (DF)_ proportion (PLAND), evergreen forest (EF)_PLAND, mixed forest (MF)_PLAND, grassland (GL)_PLAND, pasture and hay (PH)_PLAND, and cultivated land (CL)_PLAND

Table 1-4 (cont'd)

LLCom^2 [i]: Landscape-level Composition^2: DF_PLAND^2, EF_PLAND^2, MF_PLAND^2, GL_PLAND^2, PH_PLAND^2, and CL_PLAND^2

CLCon [j]: Class-level Configuration: DF_ median patch area (AREA_MD), DF_ CV of patch areas (AREA_CV), DF_ mean shape index (MSI), EF_ AREA_MD, EF_ AREA_CV, EF_ MSI, EF_ CWED, MF_ AREA_MD, MF_ AREA_CV, MF_ MSI, and MF_ CWED

The random effects structures for all models included random intercepts for township and year, and a random slope for the time trend covariate. Across the 7 climate-ecozones, the time trend random slope had low estimated variance. Variation not accounted for by fixed-effects covariates was greater for time (i.e., yr intercept) than space (i.e., township intercept), except for the St. Lawrence Plain and Champlain Valley and Great Lakes Plain climate-ecozones.

DISCUSSION

Our goal was to assess the influences that weather, landscape-level habitat characteristics, and their interactions have on harvest to inform managers of characteristics that can be managed and as managers re-examine fall harvest regulations. Our findings show that spring weather and landscape-scale habitat characteristics are significant drivers of fall harvest and that their interaction is central to understanding their impact. However, our results also show that the suite of factors affecting fall harvest varies among climate-ecozones, with some variables showing large areas of continuity and others showing importance in limited contexts. A major strength of our climate-ecozone-specific approach is that we were able to examine a large extent that stretched across climate regions and ecoregions, while determining important differences in major drivers among climate-ecozones. This added robustness to our models and broadened their application well beyond New York.

There are few environmental drivers that stretch across several climate-ecozones and influence harvest. Spring rainfall was the most ubiquitous environmental driver decreasing harvest across the climate-ecozones comprised of agricultural landscapes, mixed landscapes of northern hardwood forests or oak dominated forests interspersed with dairy farms, and river valleys. Roberts and Porter (2000) also successfully used weather to predict fall harvest in landscapes of the forest-agriculture matrix because of its link with nest success (Roberts and Porter 1998b) and poult survival (Roberts and Porter 1998a).

The metrics that quantified landscape-scale habitat characteristics were varied in their influences across different climate-ecozones and appeared to depend on context, specifically, which cover types were most limited on the landscape. For example, in climate-ecozones where there was a dominant cover type (e.g., forests or agriculture), forest edges and interspersion and juxtaposition of all cover types were positively related to harvest. Other heavily forested climate-ecozones (e.g., Central and Eastern Appalachians and Taconic Hills) also exhibited the importance of edges between open lands and forests. In one climate-ecozone, an intermediate density of edges (i.e., 64 m/ha) contributed to a maximum harvest: increasing edge density was positively associated with harvest, then harvest was maximized, and finally increasing edge density was negatively associated with harvest. This relationship exemplifies the idea that increasing edge density provides higher quality habitat up to a certain level (e.g., 64 m/ha) after which the larger densities of edges on the landscape is too fragmented to be considered good habitat.

In a neighboring climate-ecozone, maximum harvest was achieved at the lowest and highest density of edges: decreasing with increasing edge density, then minimized, and finally increasing with increasing edge density. This quadratic relationship is counter to the hypothesized habitat fragmentation quadratic relationship; consequently there may be more underlying complexity: edge density likely represents both wild turkey habitat and predator habitat. Perhaps in this climate-ecozone, meso-predators are able to make use of increasing edge density to find and depredate nests (Fleming 2003), which depresses fall harvest, then at a higher density of edges, wild turkeys benefitted from more edges, leading to increased harvest.

Past research also shows opposing relationships. Fleming (2003) demonstrated that when habitat was viewed across larger landscapes (i.e., 78 km^2), abrupt edges increased nest predation risk, while in 3 southwestern counties of New York, Glennon and Porter (1999) found that abrupt edges was correlated with more harvested birds. These seemingly contradictory findings concerning edges suggest that there is landscape structure diversity among ecoregions which will affect populations and levels of harvest differently.

Different types of available habitat (i.e., proportions of the different cover types) affected harvest differently across the landscapes of different climate-ecozones, similar to what was seen in previous studies (Gefell 1991, Lewis 1992, Wunz and Pack 1992). It appears that the increasing proportions of limited land-cover types increased harvest. In the southwestern northern hardwood-agricultural matrix, increasing proportions of evergreen forest increased harvest up to about 12%, after which harvest decreased. We suspect these evergreen forests function to shelter wild turkeys from the negative effects of winter wind and snow coming off Lake Erie and therefore affect harvest positively. However beyond 12% of evergreen forests decreases harvest likely because it provides little use beyond winter shelter.

It also appears that increasing proportions of land-cover types that provide important food resources (e.g., grasslands that support insect populations for poult consumption, oak woodlands with crops of acorns) increased harvest beyond the proportion they could be considered limited. In the northern hardwood-agricultural matrix (i.e., Central and Eastern Appalachians and Taconic Hills), similar to Glennon and Porter’s (1999) findings, increasing proportions of all open lands (0−65%) increased harvest. While in the river valleys, increasing proportions of mixed forest lands (0−42%) and pasture and hay lands (0−60%) increased harvest.

The effects of cover-type configurations differ among climate-ecozones. Contrary to past findings relating patch shape complexity (Fleming 2003), we found that in the northern hardwood-agricultural matrix (i.e., Eastern Appalachians and Taconic Hills), high shape complexity of evergreen forest patches was negatively associated with harvest. While in the river valleys and the highly agricultural Great Lakes Plain, high shape complexity of mixed forest patches was negatively related to harvest.

These differences in findings are likely due to several disconnects between Fleming's research and ours. The landscapes between the 2 studies are of different scales. The complexities of forest patch shapes in a township (mean size 120 km^2) likely do not impact fall harvest in the same manner that the complexity of all the patch shapes within 5 km (i.e., 78 km^2) of a nest site impacts nest predation. There is a disconnect in the coverages of the 2 studies; while Fleming (2003) placed nearly 500 nests, they were limited to 12 sites, or landscapes, while we examined 918 townships, or landscapes, spanning the entire state. Due to the limited coverage of Fleming's study, the range of values for MSI that she measured is likely a subset of the range of values that we measured. Also, Fleming combined the 3 forest classes and the agriculture classes and then calculated total MSI of the landscapes, while we examined the MSI of the 3 forest classes separately. Therefore, the range of values for MSI that Fleming measured likely is different than the range of values that we measured. Fleming interpreted the positive relationship at the smaller scale to represent a functional response of predators to more complex shapes. We interpret the negative relationships at the larger scales to represent numerical responses of predators to the habitat provided by complex-shaped forest patches.

The effects of patch area sizes of deciduous forest patches differed among climate-ecozones. For example, patches of deciduous forest increasing in size from 0.1 to 0.45 ha in the northern hardwood-agricultural matrix (i.e., Central Appalachians) and from 0.1 to 0.5 ha in the highly agricultural Great Lakes Plain were positively associated with harvest, while in the river valleys, patches of deciduous forest increasing in size from 0 to 0.3 ha were negatively associated with harvest. Perhaps larger patches provided more cover, night roosting, day resting, and food (Porter 1992) in forest-agriculture and almost exclusively agricultural landscapes, while in the agricultural and riverine landscapes, wild turkeys sought other cover-types over deciduous woodlands.

Interactions between weather and habitat were important on 2 spatial scales. By dividing the state up into 7 climate-ecozones and allowing covariate effects to be estimated separately among climate-ecozones, we accounted for possible interactions on one spatial scale. Then we explicitly tested interaction terms for all climate-ecozones and found interactions to be important at smaller spatial scales: within 2 of the 7 study areas. At the larger spatial scale (i.e., state wide), an interaction of weather and habitat was evident because spring rainfall was negatively related to harvest in 5 of the climate-ecozones that are traditionally considered optimal habitat conditions in the agriculture-forest matrix, while there was no relationship between rainfall and harvest in the 2 sub-optimal climate-ecozones. At the smaller scale (i.e., within one climate-ecozone), there was additional interaction between rainfall and habitat; in the northern hardwood-agricultural matrix (i.e., Eastern Appalachians and Taconic Hills), the increasing proportion of open lands, from 0 to 0.8, in a township was positively associated with harvest, but as June total rainfall increased from 1.1 cm to 34.9 cm, harvest was comparatively less across all proportions of open lands. In the heavily forested Adirondacks and Tug Hill, as interspersion and juxtaposition of land cover increased, harvest increased, but because June rainfall was not an important driver, June total rainfall depressed harvest in the same manner across all values of rainfall.

The near zero variance for the time trend random slope tells us that within climate-ecozones, the overall time trend patterns of harvest among townships varied little. This was probably because the general harvest trends through time were common across townships. Annually-varying drivers likely affected harvest more than drivers that are relatively static within years.

The take home messages of this study are multifold. Examining the separate questions of spring weather and landscape-level habitat characteristics effects on fall populations and subsequent harvest is not new, but the integrated manner and climate-ecozone specific approach used to address the questions allowed many relationships to be revealed. Our approach illuminated differences in the relationships between explanatory environmental variables and populations that support harvest among climate-ecozones because the relationships are context-specific, while there are also a few fundamental drivers that occur across many climate-ecozones. We found an interaction of weather and landscape-level habitat characteristics at multiple scales. Abundance, as indexed by harvest, in climate-ecozones with high-quality forest-agriculture matrix that provided good quality nesting and early brooding habitat was affected by weather, whereas abundance in climate-ecozones of comparatively poor quality habitat (e.g., highly forested) was not affected by weather. We also found that within a high-quality forest-agriculture climate-ecozone, population size increased with habitat quality, but even in high quality habitat, was suppressed by inclement weather. Populations in areas of high-quality habitat have the resources to recover their numbers in years when weather does not have detrimental effects.

CHAPTER 2: EFFECTS OF WINTER SEVERITY, AGRICULTURE, AND FALL HARVEST ON SPRING WILD TURKEY ABUNDANCE

ABSTRACT

After decades of successfully growing eastern wild turkey (*Meleagris gallopavo silvestris*) populations through trap and transfer management across their historic range, populations have experienced stabilization and, in some cases, decline. Now the management goal is to re-evaluate landscape-scale drivers of populations and set spring and fall harvest regulations accordingly. We examined spring harvest records in New York State over the period 1985−2010, evaluating the potential landscape-scale effects of spring rainfall, winter severity, land cover and configuration, the interaction between winter and land cover, productivity, and fall harvest. We used mixed-effects regression models with the negative binomial distribution to evaluate the effects of potential drivers on spring abundance, modeling spring harvest-effort data in each of 7 regions of differing climate and ecoregion characteristics. We found that winter severity (i.e., the number of days when snow depth was ≥ 25 cm) and proportion of cultivated lands (i.e., increasing from 0 to 0.55 across multiple regions in New York State) were the most wide-spread significant drivers. Winter severity was negatively associated with decreased spring abundance in the snowy, mainly northern hardwood (i.e., beech (*Fagus grandifolia*), maple (*Acer* spp.)) forested region (β = −0.078, 95% CI = −0.138 to −0.017), in the snowy higher elevation, mostly northern hardwood forested region (β = −0.042, 95% CI = −0.066 to −0.018), and the snowy, low-lying highly agricultural region (β = −0.037, 95% CI = −0.071 to −0.003). Winter severity had a quadratic relationship in the river valleys of both high urbanization and agriculture (β = 0.045, 95% CI = 0.002 to 0.089; β^2 = −0.02, 95% CI = −0.037 to −0.003). Proportion of cultivated lands was negatively associated with decreased spring abundance in 2 regions of varying amounts of northern hardwood forests interspersed with dairy farms (β = −0.023, 95% CI = −0.04 to −0.007; β = −0.047, 95% CI = −0.085 to −0.009) and had a quadratic relationship

in a region of northern hardwood forests interspersed with dairy farms (β = 0.018, 95% CI = −0.017 to 0.054; β^2 = −0.017, 95% CI = −0.033 to −0.001). Winter severity was consistently the most important driver of spring abundance. The effects of proportion of agriculture were unexpected, but likely are related to winter food availability and illegal harvest. We found no relationships between fall harvest, productivity, or drivers of fall harvest and spring abundance. Managers can use this knowledge to address concerns from hunters about their perceived effects of fall harvest on spring abundance and understand the roles that winter severity, land cover composition and configuration, and the interaction between winter and land cover have in affecting population fluctuations.

KEY WORDS

harvest management, landscape-scale habitat, *Meleagris gallopavo silvestris*, New York State, population index, winter severity

INTRODUCTION

Wild turkey (*Meleagris gallopavo*) restoration activities have all but ceased and populations are no longer growing exponentially. Some evidence suggests they may be declining (Tapley et al. 2001), or they may be entering into a pattern commonly seen in wildlife populations: temporal fluctuations of abundance due to varying environmental conditions (Caughley and Sinclair 1994). Spring harvest of wild turkeys has been used as an indicator for population abundance (Healy and Powell 1999), and because harvest has been declining in recent years while interest in spring hunting has remained strong (Tapley et al. 2001), there is a need to identify the potential drivers of decline and identify means for managing them. There are a number of different potential drivers of spring population abundance, some of which cannot be managed (e.g., winter weather). However, those of which can be managed (e.g., habitat availability and fall harvest) allow for resiliency of wild turkey populations towards those unmanageable drivers. The effects of fall harvest on populations have long been of concern, especially now as populations are changing. Winter severity may have a lasting effect on populations. Agricultural lands may provide important elements of winter habitat and may mitigate the effects of winter severity on spring populations. To date, there are no studies of landscape-scale effects of fall harvest, winter severity, and winter severity from a previous year, agricultural lands, or the possible interaction between winter severity and agricultural lands and its effects on spring populations. The long-term, state-wide data sets in New York provided the unique opportunity to study those effects, and the findings are applicable to the many forest-agriculture landscapes where eastern wild turkey populations have been restored but may be affected to varying degrees by winter conditions: the Great Lakes and Northeastern US regions. Winter conditions may be severe enough to constantly suppress populations (Austin and DeGraff 1975), or severe winters may be infrequent enough that populations in high-quality habitat grow during years of mild winters and are reduced in years of severe winters. These areas represent 35% of the wild turkeys in North America and 48% of all spring hunters (Tapley et al. 2011).

Weather has been identified in a number of studies as a major driver affecting wild turkey ecology. Spring rainfall is a successful predictor of fall harvest (Roberts and Porter 2000, Chapter 1) due to its link to nest success and poult survival (Roberts and Porter 1998a;b), and may be an important factor affecting subsequent spring abundance as well. Turkeys that survive the effects of spring weather must then contend with winter conditions. Eastern wild turkeys of northern lattitudes do not settle on their severely reduced winter range (Porter 1977) until there is snow on the ground, and in winter they congregate in large flocks (Healy 1992a). Wild turkeys have adapted to the climate conditions of northern lattitudes, but when harsh conditions are persistent there may be detrimental effects. Severe winters (i.e., persistently deep snow causing long-term inaccessibility of ground forage) may cause a decline in spring populations because wild turkeys have lower survival during harsh winters (Wunz and Hayden 1975, Porter et al. 1980, Porter et al. 1983).

Landscape composition and configuration have also been linked with many aspects of wild turkey ecology. Landscape composition that includes important cover types measures landscape-level habitat availability while configuration of cover types measures habitat accessibility. High-quality landscape-scale wild turkey habitat at the township extent is composed of both forested areas (between 15 – 35%) and open areas (between 25 – 40%; Porter 1992, Porter and Gefell 1996, Glennon and Porter 1999, Norman and Steffen 2003), particularly agriculture. Agriculture can be important in affecting spring populations because it buffers the effects of a severe winter when corn fields left standing provide food above the snow level (Porter et al. 1980) or when waste grain provides an important supplement to natural food sources (Vander Haegen et al. 1989) beneath snow or during mid-winter thaws.

Spring abundance may be affected by additional measures of landscape composition and configuration that influence nesting success and brood survival and are thus reflected in fall harvest in the prior year. In New York, these measures have been shown to include proportions of cover types (Porter and Gefell 1996), density of edges between forested and open cover types (Glennon and Porter 1999, Fleming 2003), interspersion and juxtaposition of cover types (Glennon and Porter 1999), and area (Wigley et al. 1985) and shape (Fleming 2003) of cover-type patches. Forested cover types (e.g., deciduous) and open cover types (e.g., grassland) must be present in the necessary proportions (Porter 1992, Porter and Gefell 1996), and the types that are lower in proportions will be the likeliest drivers to their possible status as limiting factors.

Patches of cover types must be accessibly-configured in relation to patches of other cover types. There are a number of measures of landscape-level (i.e., all cover types of interest are examined simultaneously) and class-level (i.e., only one cover type is examined at a time) configuration that are likely drivers of spring abundance. A higher density of edges between forested cover types and open cover types and interspersion and juxtaposition of all cover types on the landscape represents higher habitat accessibility and therefore are positively associated with fall harvest (Glennon and Porter 1999, Chapter 1), while the density of edges between all cover types on the landscape represents highly fragmented landscapes and therefore are negatively associated with fall harvest (Chapter 1).

Landscape configuration at the class level also drives wild turkey abundance. The density of edges between particular forest types (e.g., deciduous) and all open types allows higher habitat accessibility for turkeys and therefore is positively associated with fall harvest, and the patch sizes of cover types and the variation of patch sizes (e.g., $0.1 - 0.55$ ha) of cover types affect fall harvest differently depending on cover type (Chapter 1), while the complexity of forest patch shapes is negatively associated with fall harvest (Chapter 1).

Productivity and harvest activities may each have effects on spring abundance. It is likely that productivity in one year affects spring abundance of the subsequent year because as both juvenile and adult males comprise spring harvest, the number of available juvenile males during spring harvest is directly linked to successful reproduction. However, the birds are only available to harvest in the spring if they survive the previous fall harvest season. Healy and Powell (1999) found that a harvest of < 10% of the population is compensatory. However, the proportion of the population harvested in the fall is unknown, and therefore there has been concern that fall harvest of wild turkeys affects populations available for spring harvest.

Wild turkey populations are affected by drivers depending on geographic and climate contexts. Latitudinal and altitudinal differences across the range of the eastern wild turkey necessitate that populations will experience different climate and weather (Healy 1992b). Population numbers in areas of commonly severe weather are kept low due to low survival (i.e., 0.55 – 0.75; Austin and DeGraff 1975), while populations under generally favorable conditions expand to large numbers, intermittently reduced by severe weather events or seasons (Wunz and Hayden 1975, Healy 1992b). Similarly, different landscapes have varying levels of wild turkey habitat and therefore support varying population levels. The drivers of populations are likely limitedly available or accessible (Chapter 1). Therefore, we anticipated there would be region-specific sets of drivers, and we anticipated that weather affected spring abundance with a greater magnitude than habitat.

Some drivers affect populations at larger scales: across multiple climate and geographic zones. Geographic areas of similar landscapes and regions of similar climates should have similar drivers. Therefore, we anticipated that a few large-scale drivers affected spring abundance across multiple regions, having a ubiquitous effect on populations.

It is important to identify, and then essential to manage for, the effects of the major drivers of spring abundance because wild turkeys have been a successful story of ecological restoration and are an important resource. New York State provides an ideal opportunity to examine the potential landscape-scale drivers of spring wild turkey populations because they have fine-scale, state-wide, and decades-long spring harvest, fall harvest, and productivity data.

The objectives for this study were to 1) determine if winter severity was the major driver of spring abundance and at what spatial scale; 2) determine if agricultural lands mitigated the effects of winter severity and at what scale (i.e., were some parts of the state less affected by weather), and 3) determine if fall harvest affected spring populations.

STUDY AREA

The study area was the state of New York which is characterized by multiple climate regions (Thompson 1966), ecoregions (Bailey 1995), and agricultural regions (Thompson 1966). Approximately 25% of the land area in New York State were farms, but due to the land practices of farmers, only 18% of New York was cultivated (DiNapoli and Bleiwas 2010). We divided the study area into 7 regions based on similarity of climate, ecoregion character, and agricultural attributes (Chapter 1). The Southwest region was characterized by wet summers and snowy winters in northern hardwood forests (i.e., beech (*Fagus grandifolia*) and maple (*Acer* spp.)) and oak (*Quercus* spp.) and northern hardwood forests. The forests were interspersed with farms of < 65 hectares in size and predominately dairy, growing forage crops (e.g., clover, alfalfa), with some wheat and potato crops in the valleys. The Allegany State Park, 26,180 hectares, lies in the Southwest region and was mostly forested. The Central Appalachians region was characterized by snowy winters and geographically-variable summer moistures. The forests were mostly oak and northern hardwood interspersed with dairy farms of average size of 65 hectares. The Eastern Appalachians and Taconic Hill region, was characterized by snowy winters and wet summers in mostly northern hardwood forests with some oak and northern hardwood forests. The forests were interspersed with dairy farms larger than 65 hectares. The Catskill Forest Preserve, 116,350 hectares, lain within the mostly non-agricultural Catskill Park of the Eastern Appalachians. The Hudson and Mohawk River Valleys was a region composed of river valleys and large urban centers, and the Hudson Valley had farms of about 40 hectares for dairy, poultry, fruit and vegetable growing, while the Mohawk Valley was dominated by dairy farms 70 hectares in size.

This region was considered a transition zone because it experienced variable degrees of winter and summer precipitation. The Great Lakes Plain region was characterized by dry summers and snowy winters, in an almost entirely agricultural region of fruit, vegetable, grain and dairy farms of 45 – 60 hectares in size, with remnants of northern hardwood forests. The Adirondacks and Tug Hill region had snowy winters and wet summers and was mostly evergreen and mixed forests of spruce, fir, and northern hardwood. The St. Lawrence Plain and Champlain Valley region was characterized with snowy winters and dry summers, had large dairy farms of 75 hectares and northern hardwood forests. Farms across the state suffered abandonment over the past several decades resulting in conversion back to forests (DiNapoli and Bleiwas 2010).

There was spring harvest data for 1985−2010 for all regions except the St. Lawrence Plain and Champlain Valley where data were available for 1990−2010. In the Southwest there was spring harvest data for 107 townships (n = 2659); Central Appalachians: 77 townships (n = 1878); Eastern Appalachians and Taconic Hills: 228 townships (n = 5439); Hudson and Mohawk River Valleys: 104 townships (n=2123); Great Lakes Plain: 176 townships (n = 2436); Adirondacks and Tug Hill: 122 townships (n = 1460), and in the St. Lawrence Plain and Champlain Valley there was spring harvest data for 65 townships (n = 997).

METHODS

Data Acquisition

Spring abundance index: harvest-effort data. – We used total numbers of wild turkeys harvested and reported each spring as the response variable. NYS DEC mandates that hunters report harvests by mail, phone or internet. We summed the number of recorded harvested birds for each township (n = 879) and year (from 1985–2010). We aggregated counts at the township level to make the results comparable with previous studies. We used number of days afield for the effort data. Each reported harvest included the number of days afield before a bird was taken. The data were incorporated as the total number of days all hunters hunted in each township for each year (i.e., hunter days).

Weather and landscape-level habitat data. – We used snow depth data from 30 NYS DEC weather stations at point locations across New York State. Snow deeper than 25 cm severly limits the movement of wild turkeys (Austin and DeGraff 1975), and long periods of time in which there is deep snow decrease survival (Wunz and Hayden 1975). For each location and winter, we calculated the number of days between November 1 and April 30 that the snow depth was ≥ 25 cm. Then we interpolated those values to a continuous prediction surface using ordinary co-kringing with secondary information (Goovaerts 1997; i.e., continuous elevation data obtained from NYS DEC) using the Geostatistical Analysit tool in ArcGIS 10.2 (ESRI 2014). No transformation or trend removal was performed on either snow depth or elevation, and the default options provided by the tool were used. Visual examination of the prediction surfaces proved the use of elevation to be reasonable to predict snow depth days. Using the Zonal Statistics tool in ArcGIS, we computed the mean snow depth days for each township. The snow depth days from a winter were paired to the immediately-following spring harvest count (e.g., the snow depth days from winter November 1, 1996 – April 30, 1997 were paired to spring harvest of 1997). Additionally, the snow depth days from a previous winter were paired to a spring harvest with one-year lag (e.g., the snow depth days from winter November 1, 1995 – April 30, 1996 were paired to spring harvest of 1997).

We used Oregon State University's Parameter-elevation Regressions on Independent Slopes Model (PRISM) climate mapping system (PRISM Climate Group 2012) weather data to quantify spring rainfall. We obtained raster data for May and June total rainfall from PRISM, and following the methods of Chapter 1, averaged the total rainfall for each month and year using the Zonal Statistics tool in ArcGIS 9.3 (ESRI 2011). We paired the rainfall totals for May and June from one year to the spring harvest counts of the following year (e.g., the total rainfall from May 1996 was paired to spring harvest of 1997). Spring rainfall is a driver of fall harvest in 5 of the 7 regions, and was therefore only hypothesized to affect spring abundance in that subset (Chapter 1; Table 2-1).

Table 2-1. Drivers of fall harvest of wild turkeys in New York State during 1985-2010 in each of 7 regions.

Region	Covariates
Southwest	JR [a] + ED [b] + ED^2 [c] + EF_PLAND [d] + EF_PLAND^2 [e] + MF_PLAND [f] + DF_AREA_CV [g] + EF_AREA_MD [h] + EF_AREA_CV [i] + MF_AREA_MD [j]
Central Appalachians	MR [k] + ED + CWED [l] + CWED^2 [m] + O_PLAND [n] + F_PLAND [o] + F_PLAND^2 [p] + EF_CWED [q] + DF_AREA_MD [r]
Eastern Appalachians and Taconic Hills	MR + JR + ED + ED^2 + CWED + CWED^2 + IJI [s] + O_PLAND + O_PLAND^2 [t] + EF_CWED + EF_MSI [u] + EF_AREA_MD + (MR × EF_CWED) + (MR × IJI) + (JR × O_PLAND) + (JR × IJI)
Hudson and Mohawk River Valleys	MR + PH_PLAND [v] + GL_PLAND [w] + DF_PLAND [x] + EF_PLAND + EF_PLAND^2 + MF_PLAND + MF_CWED [y] + MF_MSI [z] + DF_AREA_MD
Great Lakes Plain	MR + CWED + CWED^2 + IJI + EF_CWED + MF_MSI + DF_AREA_MD
Adirondacks and Tug Hill	JR + CWED + IJI + (JR × IJI)
St. Lawrence Plain and Champlain Valley	GL_PLAND + GL_PLAND^2 [aa] + MF_PLAND + MF_PLAND^2 [bb]

JR [a]: June rainfall

ED [b]: Landscape-level edge density

ED^2 [c]: Landscape-level edge density ^{2}

EF_PLAND [d]: Proportion of evergreen forest

EF_PLAND^2 [e]: Proportion of evergreen forest ^{2}

MF_PLAND [f]: Proportion of mixed forest

Table 2-1 (cont'd)

DF_AREA_CV [g]:	CV of deciduous forest patch areas
EF_AREA_MD [h]:	Median patch area of evergreen forest
EF_AREA_CV [i]:	CV of evergreen forest patch areas
MF_AREA_MD [j]:	Median patch area of mixed forest
MR [k]:	May rainfall
CWED [l]:	Landscape-level contrast-weighted edge density
$CWED^2$ [m]:	Landscape-level contrast-weighted edge density ^{2}
O_PLAND [n]:	Proportion of open lands
F_PLAND [o]:	Proportion of forest lands
F_PLAND^2 [p]:	Proportion of forest lands ^{2}
EF_CWED [q]:	Contrast-weighted edge density of evergreen forest
DF_AREA_MD [r]:	Median patch area of deciduous forest
IJI [s]:	Interspersion and juxtaposition
O_PLAND^2 [t]:	Proportion of open lands^2
EF_MSI [u]:	Evergreen forest mean shape index
PH_PLAND [v]:	Proportion of pasture and hay
GL_PLAND [w]:	Proportion of grassland
DF_PLAND [x]:	Proportion of deciduous forest
MF_CWED [y]:	Contrast-weighted edge density of mixed forest
MF_MSI [z]:	Mixed forest mean shape index
GL_PLAND^2 [aa]:	Proportion of grassland ^{2}
MF_PLAND^2 [bb]:	Proportion of mixed forest ^{2}

We used land-cover and land-use data from National Land Cover Database and Coastal Change Analysis Program produced by the National Oceanic and Atmospheric Administration (Homer et al. 2004) to assess landscape composition and configuration. We calculated a set of landscape-level and class-level pattern metrics (Turner 1989, Yang and Liu 2005) in program Fragstats Version 3 (McGarigal et al. 2002, Marks et al. 2010) that represented composition and configuration of the land cover and land use classes within each township (i.e., landscape extent). The methods follow the methods of Chapter 1. Of interest were the proportions and configurations of 6 land cover classes: cultivated land, grassland, pasture/hay, deciduous forest, mixed forest, and evergreen forest. Fall harvest in each of the 7 regions is driven by a different set of landscape composition and configuration measures, so the subset of drivers differs among the regions (Table 2-1).

Fall harvest data. – We acquired fall wild turkey harvest data to use as an explanatory variable from the NYS DEC for 1984−2009. We paired the total number of birds harvested in a township for each fall with the subsequent spring harvest (e.g., fall harvest from 1996 was paired to spring harvest of 1997).

Productivity data. – We used 3 measures of wild turkey productivity. We acquired brood data from NYS DEC from 1996−2010. First we summed the number of brood flocks counted in August for each township and year, and we paired the total number of brood flocks counted in a township each August with the subsequent spring harvest (e.g., brood counts from 1996 were paired to spring harvest of 1997). Second, each spring harvest record included age and sex information. We used the total number of juvenile males harvested in the spring for each township and year. Finally, we summed the number of adult males harvested in the spring for each township and year and then used the ratio of total juvenile males to total adult males for each township and year.

Statistical Modeling

We fit mixed-effects linear models with the negative binomial distribution to model the effects of covariates on spring harvest and incorporated the natural logarithm of effort as an offset. We used the glmmADMB package (Skaug et al. 2013) written for use in program R version 2.15.3 (R Development Core Team 2010) to call AD Model Builder (http://admb-project.org, accessed December 2013; Fournier et al. 2012). The total number of harvested birds was the response variable. The total number of hunter days was used as effort information. Effort is an essential piece of the equation for using harvest as an index to abundance: H=qEN (Maunder and Punt 2004). We assume that the harvest-to-effort ratio is proportional to abundance, and catchability (q) is constant because we have no information on catchability and therefore that represented the most parsimonious model. Constant catchability of turkeys assumes that turkeys are not easier or more difficult to harvest at any time or place over another time or place.

The negative binomial distribution allowed the variance to be greater than the mean, which is common in count distributions. We tested 4 parameterizations of the negative binomial distribution, linearly-increasing variance, linearly-increasing variance with zero-inflation, quadratically-increasing variance, and quadratically-increasing variance with zero-inflation. We used Akaike's information criterion (AIC; Burnham and Anderson 2002) to chose among the 4 variance structures for each of the 7 regions.

Then we tested 4 random effects structures with the full suite of fixed effects (i.e., ecological covariates) and the top variance structure for each of the 7 regions. The first random effects structure was the simplest (eq 2-1): there was temporal variability only with year-varying intercepts. The second random effects structure had spatial variability only (eq 2-2) with township-varying intercepts (Bolker et al. 2013, Irwin et al. 2013). The third random effects structure included both temporal and spatial variability (eq 2-3) with township-varying intercepts and year-varying slope by each township (Bolker et al. 2013, Irwin et al. 2013). The last random effects structure was the most complex (eq 2-4) and included both temporal and spatial variability but accounted for the most variability possible in the system with intercepts and slopes varying among years and townships (Bolker et al. 2013, Irwin et al. 2013). We used AIC to chose among the 4 random effects structures for each of the 7 regions. Additionally, we used a log link to model the expected value of spring abundance as a function of the covariates:

$$\ln(\mu_{ij}) = \ln(\text{effort}_{ij}) + \beta_0 + b_j + \Sigma^{C}_{c=1} \beta_c X_{cij}, \qquad \text{eq 2-1}$$

$$\ln(\mu_{ij}) = \ln(\text{effort}_{ij}) + \beta_0 + a_i + \Sigma^{C}_{c=1} \beta_c X_{cij}, \qquad \text{eq 2-2}$$

$$\ln(\mu_{ij}) = \ln(\text{effort}_{ij}) + \beta_0 + t_i \text{Yr}_j + \Sigma^{C}_{c=1} \beta_c X_{cij}, \qquad \text{eq 2-3}$$

$$\ln(\mu_{ij}) = \ln(\text{effort}_{ij}) + \beta_0 + a_i + b_j + t_i \text{Yr}_j + \Sigma^{C}_{c=1} \beta_c X_{cij}, \qquad \text{eq 2-4}$$

in which effort_{ij} was the number of hunter days at township i in year j; β_0 was the intercept; a_i was the random intercept for township i (constant across time); b_j was the random intercept for year j (constant across townships); t_i was the random slope for the linear time trend at township i, and β_c was the effect of covariate X_c on spring abundance; and C is the total number of covariates (included the fixed effect average time trend across all townships). We assumed the random intercepts and slope for all mixed-effects models to be independent and identically-distributed normal random effects (e.g., $a_i \sim N(0,\sigma^2_a)$; Irwin et al. 2013).

Using the top error structure and random effects structure for each of the 7 regions, we ran a series of 67 models that represented the a priori set of competing ecological hypotheses (Table 2-2). Winter severity covariates were snow depth days (SDD) from the immediately preceding winter, its quadratic SDD^2, and the year lag of winter severity (Lg SDD; i.e., snow depth days from 2 winters previous) and its quadratic (Lg SDD^2). Agriculture covariates were: proportion of cultivated land (CL_PLAND) and its quadratic (CL_PLAND^2). (The land-cover and land-use data do not differentiate among crop types or gathering methods.) The proportion of cultivated land from 2 winters previous (Lg CL_PLAND) and its quadratic (Lg CL_PLAND^2) were only used in models that tested the significance of an interaction between Lg SDD and proportion of cultivated land. The interactions included the main effects of either SDD or Lg SDD and either CL_PLAND or Lg CL_PLAND from the same calendar year as the start of winter. The measures of productivity were: brood flock count from preceding August (BF), total juvenile males (JM) in the current spring harvest, and the ratio of juvenile males to adult males (JAM) in the current spring harvest. Total fall harvest from the previous calendar year (FH) was in one third of the models, but never in models that included the drivers of fall harvest because of the correlated nature of both categories. The drivers of fall harvest (DFH) were many and were composed of a different set for each of the 7 regions (Table 2-1). Spring rainfall covariates were May rainfall (MR) and June rainfall (JR). Landscape composition covariates were proportions (PLAND) of the following: evergreen forest (EF_PLAND), mixed forest (MF_PLAND), deciduous forest (DF_PLAND), pasture and hay (PH_PLAND), grassland (GL_PLAND), all forest lands (F_PLAND), and all open lands (O_PLAND). To test for non-linear relationships, we included the following quadratic terms: O_PLAND^2, F_PLAND^2, MF_PLAND^2, and GL_PLAND^2. Landscape-level configuration covariates were: edge density (ED), contrast-weighted (CW)ED, interspersion and juxtaposition, IJI, and the quadratic terms ED^2 and $CWED^2$. Class-level configuration covariates were: the median patch areas (AREA_MD) of evergreen forest (EF_AREA_MD), mixed forest (MF_AREA_MD), and deciduous forest

(DF_AREA_MD), the coefficient of variation of EF and DF patch areas (_AREA_CV), the mean shape index (_MSI) of EF and MF, and EF_CWED and MF_CWED.

Table 2-2. Model set for analysis of drivers of spring abundance of wild turkeys in New York during 1985-2010 in each of 7 regions. Models below are for fixed effects only. The random effects were the same across all models within the set.

Model
Y [a] + FH[b] + CL_PLAND [c] + SDD [d] + Lg SDD [e] + CL_PLAND^{2} [f] + SDD^{2} [g] + Lg SDD^{2} [h] + (CL_PLAND × SDD) + (SDD × Lg SDD)
Y + FH+ Lg CL_PLAND [i] + SDD + Lg SDD + Lg CL_PLAND^{2} [j] + SDD^2 + Lg SDD^2 + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)
Y + FH+ CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2
Y + FH+ CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)
Y + FH+ SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)
Y + FH+ Lg CL_PLAND + Lg SDD + Lg CL_PLAND^2 + Lg SDD^2 + (Lg CL_PLAND × Lg SDD)
Y + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2
Y + FH+ CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)
Y + FH+ CL_PLAND + SDD + CL_PLAND^2 + SDD^2
Y + FH+ CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2
Y + FH+ SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)
Y + FH+ SDD + Lg SDD + SDD^2 + Lg SDD^2
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)
Y + FH+ CL_PLAND + SDD + Lg SDD
Y + FH+ CL_PLAND + SDD + (CL_PLAND × SDD)
Y + FH+ SDD + Lg SDD + (SDD × Lg SDD)
Y + FH+ Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)

Table 2-2 (cont'd)

$Y + CL\_PLAND + SDD + Lg\ SDD + (CL\_PLAND \times SDD)$

$Y + CL\_PLAND + SDD + CL\_PLAND^2 + SDD^2$

$Y + CL\_PLAND + Lg\ SDD + CL\_PLAND^2 + Lg\ SDD^2$

$Y + SDD + Lg\ CL\_PLAND + Lg\ SDD + (Lg\ CL\_PLAND \times Lg\ SDD)$

$Y + SDD + Lg\ SDD + SDD^2 + Lg\ SDD^2$

$Y + FH + CL\_PLAND + SDD$

$Y + FH + CL\_PLAND + Lg\ SDD$

$Y + FH + CL\_PLAND + CL\_PLAND^2$

$Y + FH + SDD + Lg\ SDD$

$Y + FH + SDD + SDD^2$

$Y + FH + Lg\ SDD + Lg\ SDD^2$

$Y + CL\_PLAND + SDD + Lg\ SDD$

$Y + CL\_PLAND + SDD + (CL\_PLAND \times SDD)$

$Y + SDD + Lg\ SDD + (SDD \times Lg\ SDD)$

$Y + Lg\ CL\_PLAND + Lg\ SDD + (Lg\ CL\_PLAND \times Lg\ SDD)$

$Y + FH + CL\_PLAND$

$Y + FH + SDD$

$Y + FH + Lg\ SDD$

$Y + CL\_PLAND + SDD$

$Y + CL\_PLAND + Lg\ SDD$

$Y + CL\_PLAND + CL\_PLAND^2$

$Y + SDD + Lg\ SDD$

Table 2-2 (cont'd)

Y + SDD + SDD^2

Y + Lg SDD + Lg SDD^2

Y + FH

Y + CL_PLAND

Y + SDD

Y + Lg SDD

Y + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2 + BF [k] + JM [l] + JAM [m] + DFH [n]

Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD) + BF + JM + JAM + DFH

Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD) + BF + JM + JAM + DFH

Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + BF + JM + JAM + DFH

Y + CL_PLAND + SDD + CL_PLAND^2 + SDD^2 + BF + JM + JAM + DFH

Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2 + BF + JM + JAM + DFH

Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH

Y + SDD + Lg SDD + SDD^2 + Lg SDD^2 + BF + JM + JAM + DFH

Y + CL_PLAND + SDD + Lg SDD + BF + JM + JAM + DFH

Y + CL_PLAND + SDD + (CL_PLAND × SDD) + BF + JM + JAM + DFH

Y + SDD + Lg SDD + (SDD × Lg SDD) + BF + JM + JAM + DFH

Y + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH

Y + CL_PLAND + SDD + BF + JM + JAM + DFH

Y + CL_PLAND + Lg SDD + BF + JM + JAM + DFH

Table 2-2 (cont'd)

Y + CL_PLAND + CL_PLAND^2 + BF + JM + JAM + DFH	
Y + SDD + Lg SDD + BF + JM + JAM + DFH	
Y + SDD + SDD^2 + BF + JM + JAM + DFH	
Y + Lg SDD + Lg SDD^2 + BF + JM + JAM + DFH	
Y + CL_PLAND + BF + JM + JAM + DFH	
Y + SDD + BF + JM + JAM + DFH	
Y + Lg SDD + BF + JM + JAM + DFH	

Y [a]: Yr

FH [b]: Total fall harvest from the previous calendar year

CL_PLAND [c]: Proportion of cultivated land

SDD [d]: Snow depth days (i.e., winter severity) from immediately preceding winter

Lg SDD [e]: Year lag of winter severity (i.e., snow depth days from 2 winters previous)

CL_PLAND^2 [f]: Proportion of cultivated land ^{2}

SDD^2 [g]: Snow depth days ^{2}

Lg SDD^2 [h]: Snow depth days from 2 winters previous ^{2}

Lg CL_PLAND [i]: Proportion of cultivated land from 2 winters previous

Lg CL_PLAND^2 [j]: Proportion of cultivated land from 2 winters previous ^{2}

BF [k]: Brood flock count from preceding August

JM [l]: Total juvenile males in current spring harvest

JAM [m]: Ratio of juvenile males to adult males in current spring harvest

DFH [n]: Drivers of fall harvest (comprised of a different set for each of the 7 regions)

We standardized the covariates by first subtracting the mean from each datum, and then dividing the difference by the standard deviation. We evaluated multicolinearity between all potential covariates using Pearson's product-moment correlation coefficients in program R 2.15.3 (R Development Core Team 2010). If the correlation between 2 covariates was > 0.7, we excluded one of the pair from the analysis. This threshold is conservative, because there is evidence that until correlations are > 0.8, standard error estimates are not greatly affected (Fox 2008). No covariates in the a priori set of models were correlated.

We reported on the most parsimonious model (i.e., smallest AIC) from each region and considered the relationships between covariates and spring abundance significant when the 95% confidence intervals of the coefficient estimates did not overlap 0. To evaluate the fit and assumptions of the top model from each region, we calculated root mean squared-error (RMSE; i.e., square-root of mean squared differences between observed and fitted harvest numbers) and examined diagnostic plots of Anscombe residuals (Hilbe 2011, Irwin et al. 2013).

This study was exempt from filing an Institutional Animal Care and Use Committee Animal Use Form because we used electronic data retrieved from NYS DEC.

RESULTS

The negative binomial error structures were of quadratically-increasing variance, and the random effects were either the full structure or the time-varying structure. The error structure of quadratically-increasing variance had the smallest AIC for the Eastern Appalachians and Taconic Hills, the Hudson and Mohawk River Valleys, the Adirondacks and Tug Hill, and the St. Lawrence Plain and Champlain Valley (Table 2-3). The error structure of quadratically-increasing variance with zero inflation had the smallest AIC for the Southwest, the Central Appalachians, and the Great Lakes Plain (Table 2-3). The time-varying intercept only random effects structure had the smallest AIC for the Adirondacks and Tug Hill, while the full space-time varying intercepts and slopes structure had the smallest AIC for the remaining 6 regions (Table 2-4).

Table 2-3. Model set for analysis of error structures in New York during 1985−2010 in each of 7 regions. Models below included all the random effects and the largest set of covariates. The random effects were the full space-time varying intercepts and slopes structure.

	Region													
	Southwest		Central Appalachians		Eastern Appalachians and Taconic Hills		Hudson and Mohawk River Valleys		Great Lakes Plain		Adirondacks and Tug Hill		St. Lawrence Plain and Champlain Valley	
Error structure	ΔAIC	K	ΔAIC	K	ΔAIC	K	ΔAIC	K	ΔAIC	K	ΔAIC	K	ΔAIC	K
quadratic[a]	35.4	28	19.1	27	0	34	0	28	48.2	25	0	22	0	22
quadratic with zero inflation	0	29	0	28	2.0	35	1.9	29	0	26	2	23	-[c]	-
linear[b]	80.4	28	85.8	27	88.6	34	46.0	28	121.5	25	142.3	22	35.6	22
linear with zero inflation	-	-	51.0	28	90.6	35	48.0	29	93.3	26	144.3	23	10	23

[a] Var(harvest) = $\mu(1+ \mu/\kappa)$

[b] Var(harvest) = $\phi\mu$

[c] Model failed to converge

Table 2-4. Model set for analysis of random effects structures in New York during 1985−2010 in each of 7 regions. Models below included the largest set of variables and the error structure chosen by the lowest AIC from Table 2-3.

	Region													
	Southwest		Central Appalachians		Eastern Appalachians and Taconic Hills		Hudson and Mohawk River Valleys		Great Lakes Plain		Adirondacks and Tug Hill		St. Lawrence Plain and Champlain Valley	
Random effects structure	ΔAIC	K	ΔAIC	K	ΔAIC	K	ΔAIC	K	ΔAIC	K	ΔAIC	K	ΔAIC	K
Random Int Yr [a]	11.1	27	8.4	26	145	32	51.9	26	27.8	24	0	20	3.5	20
Random Int Tn [b]	951.2	27	352.4	26	1702.2	32	318.3	26	509.1	24	56.5	20	35.8	20
Random Int Tn Random Slp Yr [c]	-[e]	-	353.8	27	1671.6	33	304.1	27	-	-	56	21	33.2	21

Table 2-4 (cont'd)

Random Int Yr & Tn Random Slp Yr & Tn [d]	0	29	0	28	0	34	0	28	0	26	0.3	22	0	22

[a] Random intercept for year: $\ln(\mu_{ij}) = \ln(\text{effort}_{ij}) + \beta_0 + b_j + \Sigma^{C}_{c=1}\beta_c X_{cij}$

[b] Random intercept for township: $\ln(\mu_{ij}) = \ln(\text{effort}_{ij}) + \beta_0 + a_i + \Sigma^{C}_{c=1}\beta_c X_{cij}$

[c] Random intercept for township and random slope for year within township: $\ln(\mu_{ij}) = \ln(\text{effort}_{ij}) + \beta_0 + t_i\text{Yr}_j + \Sigma^{C}_{c=1}\beta_c X_{cij}$

[d] Random intercept and slope for year and township: $\ln(\mu_{ij}) = \ln(\text{effort}_{ij}) + \beta_0 + a_i + b_j + t_i\text{Yr}_j + \Sigma^{C}_{c=1}\beta_c X_{cij}$

[e] Model failed to converge

Each region had a different set of drivers (i.e., top model; Table 2-5). In the Southwest, we found that year, winter severity, winter severity from the previous winter, and the interaction of winter severity from both winters were drivers of spring abundance; this model fit the data (RMSE = 5.169) compared to the mean model (RMSE = 10.663). There was an additional model ≤ 2 AIC score within the top model, but the additional covariate contributed nothing, and the strength and direction of the significant drivers were similar to the top model. This is important to note because it suggests that the top model captures the drivers and their effects as well as the other competitively-ranked models.

Table 2-5. Partial model sets for the ecological structures in New York during 1985-2010 in each of 7 regions. Each of the models included all the random effects and the error structure previously chosen by AIC. Only models within 2 AIC of the top are included. K is the number of parameters; w is the model weight.

Climate-Ecozone	Model name	ΔAIC	K	w
Southwest: Cattaraugus Highlands and Allegany Hills	Y [a] + SDD [b] + Lg SDD [c] + (SDD × Lg SDD)	0	10	0.290
	Y + FH [d] + SDD + Lg SDD + (SDD × Lg SDD)	1.7	11	0.126
Central Appalachians	Y + CL_PLAND [e] + CL_PLAND^2 [f]	0	9	0.060
	Y + SDD + Lg SDD + (SDD × Lg SDD)	0.3	10	0.051
	Y + Lg SDD	0.4	8	0.049
	Y + CL_PLAND + CL_PLAND^2 + BF [g] + JM [h] + JAM [i] + DFH [j]	0.7	21	0.042
	Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2 [k]	1.2	11	0.033
	Y + SDD + Lg SDD	1.4	9	0.030
	Y + CL_PLAND + Lg SDD	1.7	9	0.025
	Y + Lg SDD + Lg SDD^2	1.8	9	0.025
	Y + FH+ CL_PLAND + CL_PLAND^2	1.9	10	0.023
	Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2 + BF + JM + JAM + DFH	1.9	23	0.023
	Y + CL_PLAND	2	8	0.022

Table 2-5 (cont'd)

Eastern Appalachians and Taconic Hills	Y + FH+ CL_PLAND + SDD + (CL_PLAND × SDD)	0	10	0.183
	Y + FH+ CL_PLAND + SDD + CL_PLAND^2 + SDD^2 [1]	1	11	0.111
	Y + CL_PLAND + SDD + (CL_PLAND × SDD)	1.4	9	0.091
	Y + FH + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2 + (CL_PLAND × SDD) + (SDD × Lg SDD)	1.6	15	0.082
	Y + FH+ CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)	2	11	0.067
Hudson and Mohawk River Valleys	Y + SDD + SDD^2	0	8	0.223
	Y + FH+ SDD + SDD^2	1.4	9	0.110

Table 2-5 (cont'd)

Great Lakes Plain	Y + CL_PLAND + SDD + CL_PLAND^2 + SDD^2	0	11	0.063
	Y + CL_PLAND + CL_PLAND^2	0.6	9	0.046
	Y + CL_PLAND	0.7	8	0.045
	Y + CL_PLAND + SDD	0.9	9	0.040
	Y + SDD + SDD^2	1	9	0.038
	Y + SDD	1.3	8	0.034
	Y + FH+ CL_PLAND + SDD + CL_PLAND^2 + SDD^2	1.4	12	0.031
	Y + CL_PLAND + Lg SDD	1.6	9	0.029
	Y + SDD + Lg SDD + (SDD × Lg SDD)	1.9	10	0.024
	Y + CL_PLAND + SDD + (CL_PLAND × SDD)	1.9	10	0.024
	Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)	2	12	0.023
Adirondacks and Tug Hill	Y + Lg SDD	0	5	0.125
	Y + SDD + Lg SDD	1.6	6	0.051
	Y + FH+ Lg SDD	2	6	0.046
	Y + CL_PLAND + Lg SDD	2	6	0.046
	Y + Lg SDD + Lg SDD^2	2	6	0.046

Table 2-5 (cont'd)

St. Lawrence Plain and Champlain Valley	Y + CL_PLAND	0	7	0.091
	Y + CL_PLAND + Lg SDD	0.6	8	0.066
	Y + CL_PLAND + SDD	1.1	8	0.053
	Y + CL_PLAND + SDD + Lg SDD	1.2	9	0.051
	Y + FH+ CL_PLAND	2	8	0.034
	Y + CL_PLAND + CL_PLAND^2	2	8	0.034

Y [a]: Yr

SDD [b]: Snow depth days (i.e., winter severity) from immediately preceding winter

Lg SDD [c]: Year lag of winter severity (i.e., snow depth days from 2 winters previous)

FH [d]: Total fall harvest from the previous calendar year

CL_PLAND [e]: Proportion of cultivated land

CL_PLAND^2 [f]: Proportion of cultivated land ^{2}

BF [g]: Brood flock count from preceding August

JM [h]: Total juvenile males in current spring harvest

JAM [i]: Ratio of juvenile males to adult males in current spring harvest

DFH [j]: May rainfall + Landscape-level edge density + Landscape-level contrast-weighted edge density + Landscape-level contrast-weighted edge density ^{2} + Proportion of open lands + Proportion of forest lands + Proportion of forest lands ^{2} + Contrast-weighted edge density of evergreen forest + Median patch area of deciduous forest

Lg SDD^2 [k]: Snow depth days from 2 winters previous ^{2}

Table 2-5 (cont'd)

SDD[2 1]: Snow depth days [2]

We found that year and a quadratic relationship of cultivated land were drivers of spring abundance in the Central Appalachians; this model fit the data (RMSE = 5.197) compared to the mean model (RMSE = 12.453). There were 10 additional models ≤ 2 AIC scores within the top model. The second to top model showed a negative relationship between winter severity of the previous winter and spring abundance. Of the 10, 4 models included the quadratic relationship between cultivated land and spring abundance, and the estimates of the linear and quadratic term were of the same strength and direction seen in the top model. Two of those 4 models also included covariates that related productivity and drivers of fall harvest to spring abundance. Each of the models showed positive relationships between brood flock numbers and spring abundance, and May rainfall and spring abundance. There were 5 additional models that had no significant drivers of spring abundance, and although they were ranked highly, the top model best captured the drivers of spring abundance. These competitive models are important to note because they confirm the relationships in the top model and suggest that there are other drivers that are masked by the effects of the main relationships.

In the Eastern Appalachians and Taconic Hills, year, fall total harvest, proportion of cultivated land, winter severity, and an interaction between proportion of cultivated land and winter severity were drivers of spring abundance; this model fit the data (RMSE = 4.809) compared to the mean model (RMSE = 11.933). There were 4 additional models ≤ 2 AIC scores within the top model. Two models exhibited estimates of the same strength and magnitude of the top model. One model found no interaction, and a u-shaped quadratic relationship between proportion of cultivated land and spring abundance, but still had a similar relationship between winter severity and spring abundance. The remaining contender had estimates for winter severity and the interaction between winter severity and proportion of cultivated land of similar strength and magnitude. However, it also showed a u-shaped quadratic relationship between proportion of cultivated land and spring abundance, and it exhibited a positive association between fall total harvest and spring abundance. These competitive models are important to note because they confirm the relationships in the top model and suggest that there could be a mitigating effect of higher proportions cultivated lands on right side of the quadratic relationship.

We found that year and a quadratic relationship of winter severity were drivers of spring abundance in the Hudson and Mohawk River Valleys; this model fit the data (RMSE = 4.28) compared to the mean model (RMSE = 10.992). There was one additional model ≤ 2 AIC score within the top model, and it had estimates of similar strength and direction as the top model.

In the Great Lakes Plain, year was a driver of spring abundance, and there were quadratic relationships between winter severity and spring abundance and between proportion of cultivated land and spring abundance; this model fit the data (RMSE = 4.599) compared to the mean model (RMSE = 12.292). There were 10 additional models ≤ 2 AIC scores within the top model; 2 models had estimates of similar strength and direction as the top model, and 8 models had no significant drivers. This is important to note because it suggests that the top model captures the drivers and their effects as well as or better than the other competitively-ranked models.

We found that year and winter severity of the previous winter were drivers of spring abundance in the Adirondacks and Tug Hill; this model fit the data (RMSE = 3.8) compared to the mean model (RMSE = 7.895). There were 4 additional models ≤ 2 AIC scores within the top model and they all had estimates of similar strength and direction as the top model.

In the St. Lawrence Plain and Champlain Valley, year and the proportion of cultivated land were drivers of spring abundance; this model fit the data (RMSE = 4.247) compared to the mean model (RMSE = 10.605). There were 5 additional models ≤ 2 AIC scores within the top model, and they had estimates of similar strength and direction as the top model.

Winter Severity

In general, where snow depth was an important driver, landscape-scale habitat characteristics were not, or depth affected regional spring abundance more strongly than landscape-scale habitat characteristics. In the Southwest winter severity correlated with decreased spring abundance (β = −0.078, 95% CI = −0.138 to −0.017, P = 0.012; Fig 2-1A), however, winter severity from the previous winter was positive, but not significant, while the interaction of winter severity from both winters was positive (β = 0.033, 95% CI = 0.004 to 0.062, P = 0.024). In the Eastern Appalachians and Taconic Hills increasing winter severity (β = −0.042, 95% CI = −0.066 to −0.018, P = 0.001; Fig 2-1B) was negatively associated with spring abundance. In the Hudson and Mohawk River Valleys there was a quadratic relationship of winter severity and spring abundance. There was an initial positive relationship, and then a negative relationship between winter severity and spring abundance (β = 0.045, 95% CI = 0.002 to 0.089, P = 0.042; β^2 = −0.02, 95% CI = −0.037 to −0.003, P = 0.019; Fig 2-1C) implying that there is an intermediate value of snow depth days which is ideal for spring abundance of wild turkeys. In the Great Lakes Plain winter severity decreased spring abundance (β = −0.037, 95% CI = −0.071 to −0.003, P = 0.033; Fig 2-1D).

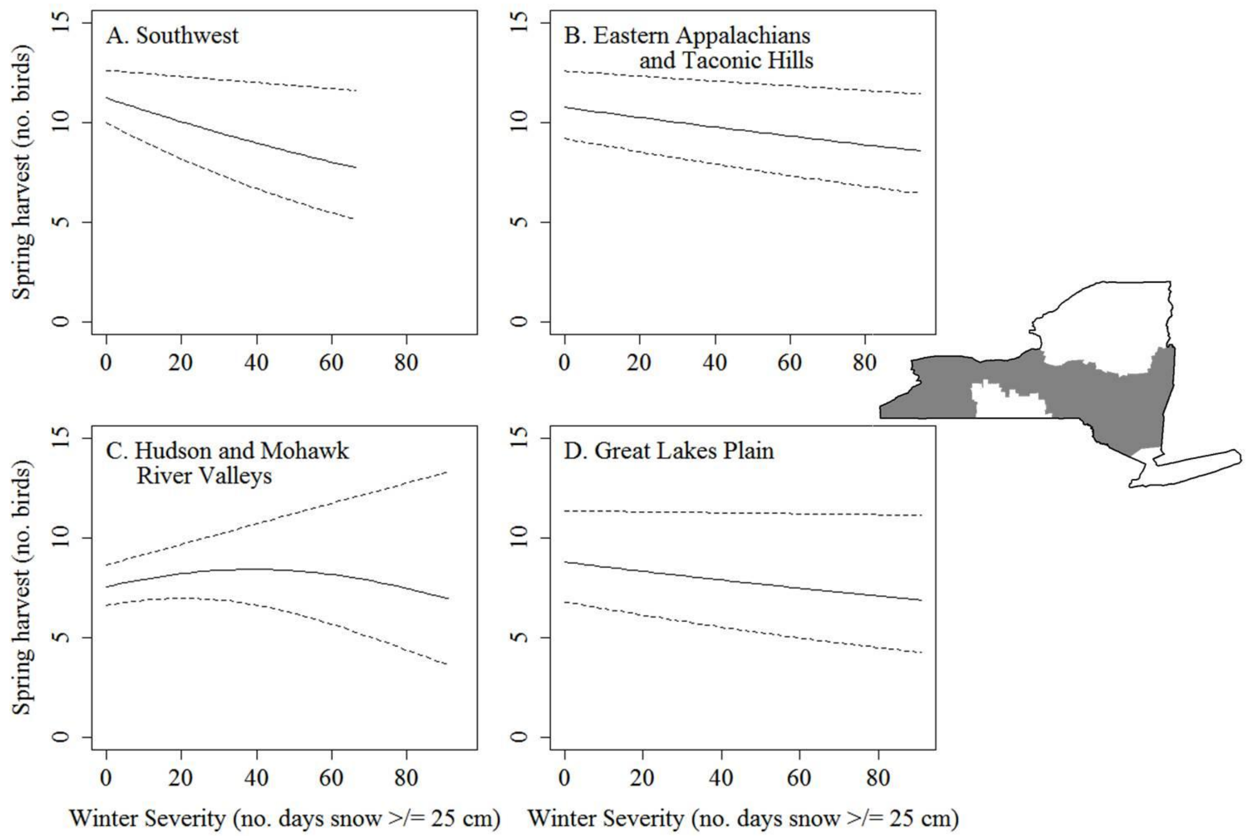

Figure 2-1. Winter severity effects on township-level spring abundance (adjusted by effort) are wide-spread across southern New York State from 1985−2010 (95% confidence intervals indicated by dashed lines). In the Southwest (A), Eastern Appalachians and Taconic Hills (B), Hudson and Mohawk River Valleys (C), and Great Lakes Plain (D) winter severity (i.e., numbers of days from Nov 1 – April 30 when the snow on the ground is ≥ 25 cm) was negatively associated with spring abundance.

Agriculture

In the Central Appalachians, as the proportion of cultivated land increased to 12-13%, spring abundance also increased (although the linear term was not precisely estimated) but only up to a certain point after which spring abundance decreased (β = 0.018, 95% CI = −0.017 to 0.054, P = 0.306; β^2 = −0.017, 95% CI = −0.033 to −0.001, P = 0.043; Fig 2-2A). In the Eastern Appalachians and Taconic Hills increasing proportion of cultivated land (β = −0.023, 95% CI = −0.04 to −0.007, P = 0.006; Fig 2-2B) was negatively associated with spring abundance. In the St. Lawrence Plain and Champlain Valley, the increasing proportion of cultivated land was negatively associated with spring abundance (β = −0.047, 95% CI = −0.085 to −0.009, P = 0.015; Fig 2-2C).

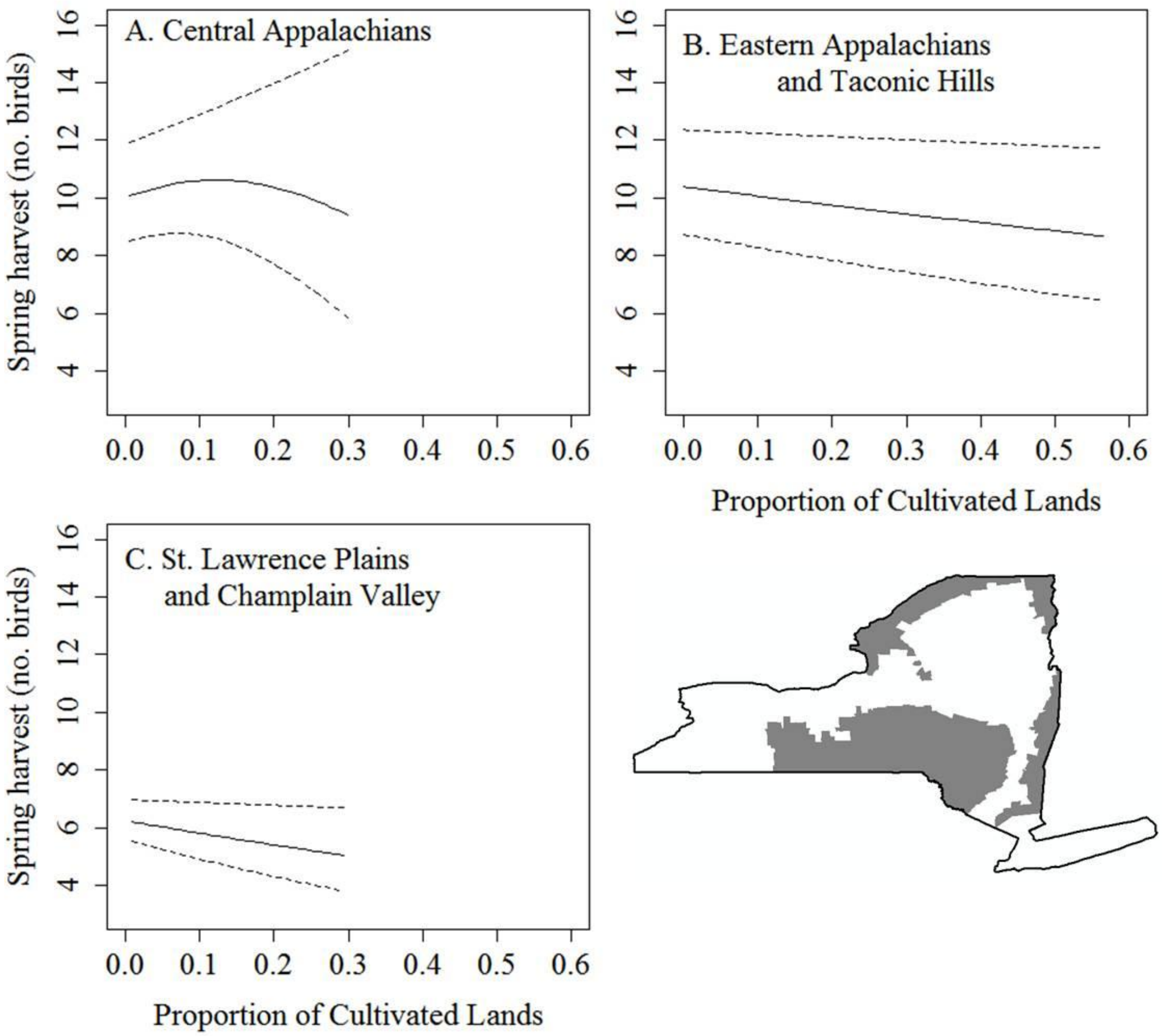

Figure 2-2. Proportion of cultivated lands effects on township-level spring abundance (adjusted by effort) in 3 regions of New York State from 1985−2010 (95% confidence intervals indicated by dashed lines). In the Central Appalachians (A), intermediate values of (12−13%) proportion of cultivated lands were associated with the highest spring abundance. In the Eastern Appalachians and Taconic Hills (B) and St. Lawrence Plain and Champlain Valley (C) increasing proportion of cultivated lands was negatively associated with spring abundance.

Interaction of Winter Severity and Agriculture

In the Eastern Appalachians and Taconic Hills the interaction of the winter severity and proportion of cultivated land was positive (β = 0.014, 95% CI = 0.003 to 0.025, P = 0.012). Here the negative effects of increasing proportion of cultivated land are exacerbated by the negative effects of winter severity (Fig 2-3).

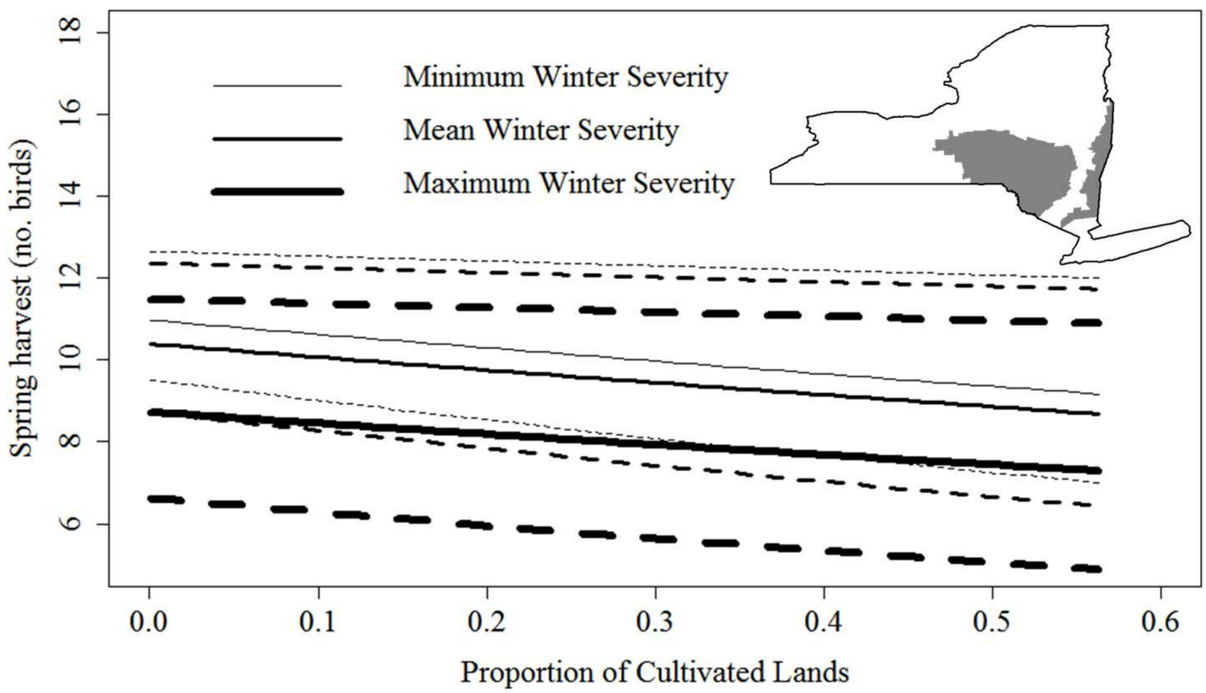

Figure 2-3. Effects of the interaction between winter severity and proportion of cultivated lands on township-level spring abundance (adjusted by effort) in the Eastern Appalachians and Taconic Hills of New York State from 1985−2010 (95% confidence intervals indicated by dashed lines). Increasing proportions of cultivated lands were negatively associated with spring abundance. As winter severity increased from the minimum (lightest solid line) to the maximum (heaviest solid line), spring abundance was suppressed and exacerbated the negative effects of increasing proportion of cultivated lands.

The major large-scale drivers that affected spring abundance across multiple regions were winter severity and the proportion of cultivated lands. In the northern regions, spring harvest increased through the study period (Table 2-6); in the Adirondacks and Tug Hill and in the St. Lawrence Plain and Champlain Valley, year was significant (β = 0.028, 95% CI = 0.007 to 0.049, P = 0.01; β = 0.035, 95% CI = 0.013 to 0.056, P = 0.002). Fall harvest, all measures of productivity, and drivers of fall harvest were not important drivers of spring abundance; fall harvest was in the top model for only one region where it was not significant (Table 2-6).

Table 2-6. Directional effects of covariate from the top models in each of 7 regions in New York during 1985−2010. The symbols are as follows: +, -, or 0 for each variable (indicating a positive coefficient, a negative coefficient, or zero for variables not included in the top AIC models, respectively). The gray shaded symbols indicate a coefficient whose 95% confidences intervals did not overlap 0.

	Region						
	Southwest	Central Appalachians	Eastern Appalachians and Taconic Hills	Hudson and Mohawk River Valleys	Great Lakes Plain	Adirondacks and Tug Hill	St. Lawrence Plain and Champlain Valley
Covariate	Direction of Effect						
Intercept	-	-	-	-	-	-	-
Y [a]	+	+	+	+	+	+	+
SDD [b]	-	0	-	+	-	0	0
SDD^2 [c]	0	0	0	-	+	0	0
Lg SDD [d]	+	0	0	0	0	-	0
SDD × Lg SDD	+	0	0	0	0	0	0
CL_PLAND [e]	0	+	-	0	+	0	-
CL_PLAND^2 [f]	0	-	0	0	+	0	0

Table 2-6 (cont'd)

CL_PLAND × SDD	0	0	+	0	0	0	0
FH [g]	0	0	+	0	0	0	0

Y [a]: Yr

SDD [b]: Snow depth days (i.e., winter severity) from immediately preceding winter

SDD^2 [c]: Snow depth days ^{2}

Lg SDD [d]: Year lag of winter severity (i.e., snow depth days from 2 winters previous)

CL_PLAND [e]: Proportion of cultivated land

CL_PLAND^2 [f]: Proportion of cultivated land ^{2}

FH [g]: Total fall harvest from the previous calendar year

DISCUSSION

This study is the first to examine the potential interaction of winter severity and landscape-level habitat characteristics and fall harvest and their population-level effects at large spatial extents. These findings are relevant across the northern parts of range of the eastern wild turkey where winter weather and the forest-agriculture matrix predominates. Biologists have been aware for decades that winter severity was a driver of wild turkey survival, and we were able to quantify how winter severity and habitat interact to affect spring populations. Winter severity is related to decreased spring abundance at a large scale across much of the study area, and cultivated lands are related to decreased abundance across other portions of the study area. Winter and agriculture interact with an unexpected relationship in a southerly region of the study area, and perhaps, as expected, in a second southerly region with optimal intermediate proportions of agriculture and no effects of winter severity. Regional differences in climate and landscapes are important to distinguish because environmental drivers have varying strength and importance among regions. These differences also help distinguish multiregional assemblages affected by similar drivers within larger extents.

The major large-scale drivers of spring abundance, reaching across several regions, were winter severity and proportion of cultivated lands. The relationship between winter severity and spring abundance was as expected; winter severity had the largest effect on spring populations, supporting past findings (Porter et al. 1983, Healy 1992b). The regions that were affected by winter severity were southerly and had fewer severe winters (i.e., higher variability of winter severity) than the 2 northerly regions that were unaffected by winter severity. The southern regions experienced extreme winters less frequently (i.e., had fewer numbers of days in which snow depth $\geq$ 25 cm) than the northern regions. Therefore, higher population numbers in the southerly regions declined in condordance with increasing winter severity, while lower population numbers in the northerly regions were unaffected by common severe conditions. This periodicity of severe conditions (i.e., many days of deep snow) reduces large populations or prevents the growth of small populations. If severe winters occur more frequently than turkey populations can grow, then turkey populations are not going to attain high numbers (Austin and DeGraff 1975). On the other hand, if severe conditions occur less frequently, then there should be more amplitude in population fluctuation.

There was one outlier region from the others; there may have been a mitigating effect of agriculture on winter severity in the Central Appalachians. The Central Appalachians experienced variable winters with similar frequencies of snow depth days as other southerly regions, but spring abundance was unaffected by winter severity. Also there was a quadratic relationship between proportion of cultivated lands and spring abundance. The ideal proportion of cultivated land in a township was between 12 and 13%; spring abundance increased as cultivated land increased from 0 to 12% and then decreased as cultivated land increased from 13 to 30%. The intermediate proportion of cultivated lands was optimal and was associated with higher spring abundance in this region, and maybe it was at this optimal proportion where turkeys most easily accessed agricultural food sources and therefore avoided the effects of a severe winter.

Proportion of cultivated lands was the other major large-scale driver. In the remaining 2 regions where it was important (i.e., Eastern Appalachians and Taconic Hills and St. Lawrence Plain and Champlain Valley), it affected spring abundance negatively across all proportions of cultivated land. Here there may be a couple of processes at work. Turkeys likely foraged on forest resources during the winter because manure spreading in agricultural fields was no longer pervasive. Additionally, forests provide ground forage when there is little snow and where there is surface water at springs and seeps (Healy 1992a). When the snow is deep and persistent, turkeys can remain at roost and forage on stems, buds, and fruits that are retained on shrubs and trees (e.g., dogwood, sumac, beech, barberries) through the winter (Healy 1992a, Hurst 1992, Wunz and Pack 1992).

Perhaps the negative relationship between cultivated lands and spring abundance is a manifestation of poaching loss. The underlying mechanism could be associated with the features of cultivated lands that increase visibility of turkeys and their vulnerability to poaching. Past studies in the forest-agriculture matrix landscape have documented the negative effects of poaching on wild turkey survival (Roberts et al. 1995, Vangilder and Kurzejeski 1995). Prior to strict enforcement of hunting regulations and restoration efforts, wild turkeys that had survived overharvest during the European settlement of North America were found in largely inaccessible swamp forests of the southeastern US (Hewitt 1967, Kennamer et al. 1992).

Of the regions that did not exhibit a relationship between proportion of cultivated lands and spring abundance, one was non-agricultural, and one was highly agricultural, while the remaining 2 had similar proportions to a region where spring abundance was negatively affected by proportion of cultivated land. Perhaps the buffering effects of agricultural food sources on winter survival that Porter et al. (1980, 1983) found was localized, and the food resources available on cultivated lands are not substantial enough to affect survival of populations of wild turkeys and therefore population size (Healy 1992b). Additionally, it is likely that the plots of standing corn in the Minnesota study of Porter et al. (1980, 1983) is a different resource than ground-lying waste grain which may feed other wildlife species first and is not as easily accessible as stalks of corn or fruited tree branches (Healy 1992a, Hurst 1992) standing above the snow. Wild turkeys are known to feed on vegetation matter from manure spreads on dairy farms (Vander Haegen et al. 1989), but the practice of spreading manure during the winter has declined as dairy farmlands have declined from 44% of the state in the mid 1900s (Thompson 1966) to about 25% of the state in 2010 (DiNapoli and Bleiwas 2010).

We evaluated many potential drivers. There were few other significant drivers. In the northern part of the state, spring abundance increased over the study time period likely because the north was re-colonized most recently and the small populations are still growing (Fig 2-4). Some ecologically intuitive drivers like the drivers of fall harvest, fall total harvest, and productivity appeared to play no role. Rather, what we found is that spring populations were dominated by increasing numbers of days of deep (≥ 25 cm) snow and habitat, specifically number of days with deep snow and proportion of cultivated land. There is no doubt that many factors influence population size (Healy and Powell 1999), but perhaps the most recent events drive most of the variability. Fall harvest may be compensatory and therefore too small to affect spring populations. The effects of winter severity and proportions of cultivated land on spring abundance may suppress any additional environmental effects on pre-winter population abundance.

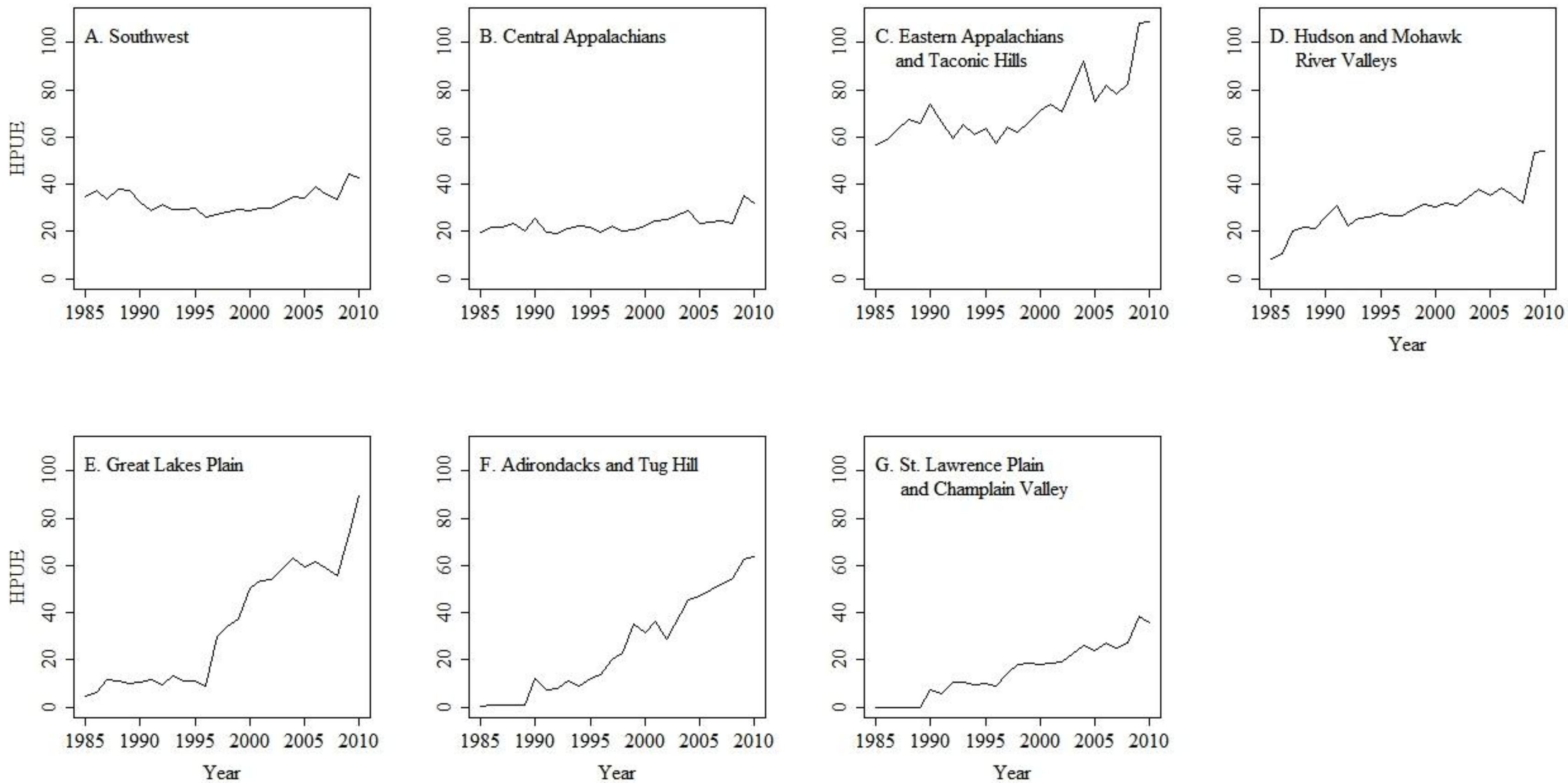

Figure 2-4. Harvest per unit effort (HPUE) for each of the 7 regions of New York State from 1985−2010.

These drivers were not consistent in every region or across the state. In the regions where winter severity, cultivated lands or either was unimportant, it is likely due to lack of variability in those drivers within those regions. While the northerly regions may experience consistent severe winters that suppress population size, the lack of variability in those data prevent us from identifying it as a driver. Similarly, the highly agricultural region and the highly forested region also do not have enough variability in the proportions of cultivated land, and prevent identification as a driver.

We identified the region-specific and larger-scale effects of winter severity on spring abundance and the possible mitigating effects of agriculture on winter severity in one region while identifying the detrimental effects of agriculture in other regions. Winter severity is the most far-reaching driver of spring eastern wild turkey populations in the forest-agriculture landscapes that experience variability in winter severity over time. In landscapes of consistently severe winters (i.e., many days of snow depth $\geq$ 25 cm), severity had no apparent effect on year to year abundance. Cultivated lands are avoided perhaps due to a number of reasons; there may be little food left during winter due to farming practices, or forests provide other sources of winter foods and thermal cover. Perhaps the negative relationship is a reflection of where turkeys are illegally harvested. However, legal fall harvest had no apparent effect on spring populations. We had expected the drivers of spring abundance to be similar across larger extents, but not identical in their effects, so dividing the study area in regions allowed us to identify the region-specific and statewide drivers and the differences in their magnitudes of effects on spring abundance.

CHAPTER 3: BROODING OVER BROODS: REGIONAL IMPACTS OF HABITAT QUALITY ON WILD TURKEY PRODUCTIVITY

ABSTRACT

Eastern wild turkey populations (*Meleagris gallopavo silvestris*) appear to be declining across much of their range. We anticipated that a key driver of decline may be a reduction in reproductive success. Past research has shown that aspects of productivity are related to habitat and weather, but the relative importance of these factors has not been assessed. High-quality habitat for eastern wild turkeys has structural heterogeneity with high interspersion of open and forest cover types. May precipitation is thought to influence rates of nest predation, and June precipitation affects poult survival and thus both may be major drivers of productivity. Our objective was to evaluate the relative contributions of habitat quality and precipitation to productivity as reflected by August brood counts (i.e., the number of broods observed per township each August). We assessed habitat quality using 3 land-cover pattern metrics and a moving-window approach for land cover across New York State (NYS), applying 5 window sizes, representing different scales (1 km, 5 km, 10 km, 15 km, and 20 km radii), to test their potential effects on productivity. After determining the influential landscape scales, we tested the effect of spring weather with May and June total rainfalls and minimum temperatures and the possible interaction effects of weather and landscape. We assessed the fit of multiple models relating linear and nonlinear contributions of habitat quality and precipitation to New York brood counts collected at the township level from 1996–2009 using the suitable negative binomial distribution in generalized linear mixed-effects models. Results showed good model fit across the state. Interspersion and juxtaposition of 6 land-cover types is a main driver of productivity state-wide ($\beta = -0.014$ 95% CI = −0.067 to 0.039, $P = 0.611$, $\beta^2 = -0.037$, 95% CI = −0.062 to −0.012, $P = 0.004$), and in the southern high-quality habitats with larger brood counts ($\beta = 0.03$ 95% CI = −0.037 to 0.097, $P = 0.374$, $\beta^2 = -0.041$, 95% CI = −0.072 to −0.01, $P = 0.01$) and northern lower-quality habitats of smaller brood counts ($\beta = -0.097$, 95% CI = −0.173 to −0.019, $P = 0.014$) portions of NYS when examined separately. Increasing complexity of habitat patches, measured by the mean shape index, decreases productivity (i.e., brood counts) in the southern half of the state ($\beta = -0.068$, 95% CI = −0.124 to −0.012, $P = 0.017$). Habitat configuration is the main driver of productivity, and while we found no evidence for spring rainfall, we found some evidence for increasing temperatures affecting productivity. We suggest that management of habitat at the 1 km scale will increase productivity of eastern wild turkey populations.

KEY WORDS

brood flock counts, landscape, *Meleagris gallopavo silvestris*, New York State

INTRODUCTION

Wild turkey populations have been successfully restored through the efforts of many state management agencies, conservation organizations like the National Wild Turkey Federation, and university scientists. Wild turkey research identified potentially suitable habitat for translocations, and money and effort from state agencies and conservation organizations made the translocations possible. These translocations allowed population numbers to increase exponentially across the range of the eastern wild turkey. Wild turkeys are now an integral part of the eastern forest-agriculture ecosystem. However, population assessments and observations by hunters over the past 10 years suggest that wild turkey populations may be experiencing a general decline (Tapley et al 2010). Long-term data collection of brood data by the New York State Department of Environmental Conservation (NYS DEC) and an ongoing series of studies over the past 20 years provide an opportunity to explore the relative importance of habitat and weather to reproductive success of wild turkeys.

Productivity is an important population performance metric that incorporates nest success and poult survival, and can provide a harvest-independent assessment of population change. Essentially, if productivity and population abundance are related in a proportional way, then productivity could be used an index for abundance (Healy and Powell 1999). However, if turkey populations are density dependent (McGhee et al. 2008), this relationship may break down at unknown high densities where competition for nest sites, predation or some other density-dependent phenomenon may negatively affect reproductive success. Then, productivity may not be a surrogate for abundance, but rather an underlying factor that helps explain growth, abundance, and distribution. Biologists estimate productivity using brood surveys, and it is typical to monitor productivity via counts of hens and poults, or counts of broods (Healy and Powell 1999). Understanding the drivers of wild turkey productivity is essential to natural resource agency biologists. Such knowledge enables biologists to make better management decisions and prevents the deterioration of a resource that took decades to restore.

Wild turkey landscape-level habitat can be represented by landscape metrics that measure configuration of multiple land-cover types, and high-quality landscape-level habitat is characterized by land-cover types that are configured in a structurally heterogeneous way. Increasingly high interspersion of open (i.e., pasture and hay, cultivated land, and grassland) and forest (i.e., deciduous, mixed, and evergreen) cover types provides increasing access to nesting, brood rearing, roosting, and foraging sites (Lewis 1992, Wunz and Pack 1992, Glennon and Porter 1999, Fleming and Porter 2007a). However, despite extensive research on wild turkeys, little is known about how land-cover configuration influences productivity. Further, little work has been done on scale-dependency of land-cover configuration and population parameters. What scale-dependent information that is available relates to the question of nest success.

Fleming (2003) showed evidence that risk of nest predation is influenced by vegetation structure at 3 spatial scales: immediately surrounding the nest (5 – 10 m radius), characteristics of the forest patch in which the nest was lain, and landscape (i.e., 5 km radius around the nest) characteristics. She found that landscape characteristics had the largest influence on risk of nest predation.

There is sufficient evidence that inclement spring weather influences turkey productivity. For example, May precipitation is thought to facilitate nest predation through enhanced olfaction in predators during wet conditions (Miller and Leopold 1992, Roberts and Porter 1998b). Cool (7 – 11 °C; Roberts and Porter 1998a) and wet (> 12 hrs rain; Roberts and Porter 1998a) June weather decreases survival in larger poults that are unable to brood beneath their mothers (Healy and Neno 1985, Roberts and Porter 1998a, Rolley et al. 1998).

Productivity is the product of nest success and poult survival (i.e., 25 days post hatch; Roberts and Porter 1998a), and is a measure of potential recruitment into the population to be available for fall harvest. The links between productivity and nest success and poult survival compel us to hypothesize a link between productivity and landscape-scale habitat characteristics and spring weather. We examined this hypothesis by evaluating the relationships between habitat, weather, and wild turkey productivity as reflected by August brood counts (i.e., the number of broods observed per township each August) across New York State. Specifically, our objectives were to: 1) test whether scale-dependence is evident in productivity-habitat relationships, and 2) determine the relative contributions of weather and habitat and their possible interaction on productivity.

STUDY AREA

New York State is diverse both in its climate and in its landscapes but generally can be divided into northern and southern regions (Fig 3-1A). The northern part of the state has 2 distinct climate regions (Thompson 1966), and 2 distinct ecoregions (Bailey 1995). These areas include the higher elevation (~1,500 m) evergreen forests of the Adirondacks and Tug Hill and the lower elevation (< 200 m) flat and wet landscapes of the St. Lawrence Plain and Champlain Valley. The southern climate regions and ecoregions (Thompson 1966, Bailey 1995) include agricultural landscapes of the Great Lakes Plain, northern hardwood forests and dairy farms of the Cattaraugus Highlands, Allegheny Hills and the High Allegheny Plateau, the more forested Taconic Highlands, and the urbanized and riverine Hudson and Mohawk River Valleys. The southern climate regions and ecoregions also included the northern hardwood and oak forests of the Hudson Highlands, Triassic Lowlands, Manhattan Hills, and the low-lying coastal wetlands of the Coastal Lowlands.

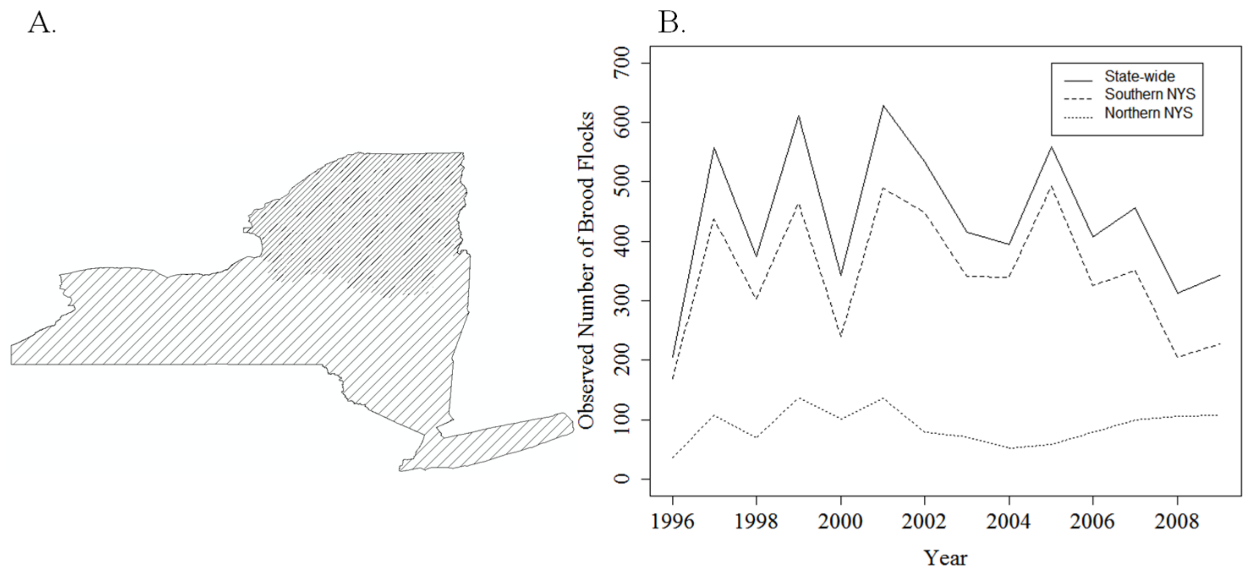

Figure 3-1. Southern and Northern New York State study regions and the observed brood flock data (A). State-wide and regional observed brood flock data are plotted for years 1996–2009 (B). Brood flock numbers fluctuate yearly in the southern region, while they stay steadier in the northern region.

METHODS

Data Acquisition

Brood survey data. – We obtained productivity data for wild turkeys from NYS DEC. These data are opportunistic sightings (i.e., en route during normal daily activities) and were collected by NYS DEC employees and members of the public during the month of August from 1996−2009. We chose brood flocks as our response variable (i.e., any flock with any number of poults was counted as 1 brood flock) because they are the most independent measure of productivity. Flocks often consist of multiple broods making it impossible to discern which poults belong to which hen, and poults are dependent on hens for their survival. Therefore, treating multiple poults or multiple broods as independent observations is likely a violation of the assumption of independence. Exploratory examination of the temporal patterns in the possible response variables (e.g. brood flocks, poults, poults per hen) showed the same directions of annual changes. We summed brood flock counts per township (i.e., the smallest unit available) per year to facilitate comparison with other wild turkey studies performed in New York State and to maximize our sample size.

Landscape-level habitat and weather data. – We obtained land-cover and land-use (LCLU) data for 2006 for New York State from the Coastal Change Analysis Program (C-CAP) produced by the National Oceanic and Atmospheric Administration (NOAA) (Homer et al. 2004). C-CAP classifies satellite imagery into 23 LCLU cover types at a 30 m^2 resolution, but for computational purposes, we changed the resolution to 100 m^2. We considered 6 of the 23 cover types as ecologically important to wild turkeys: cultivated land, pasture and hay, grassland, deciduous forest, evergreen forest, and mixed forest. These types provide resources, however different in importance, for wild turkeys. The remaining cover types were treated as background in the subsequent metric calculations. We excluded the shrubland cover type from our analysis because C-CAP only classified 3.4% of the imagery as shrub. The study area lies across 3 different C-CAP classification zones (63, 64, and 65), and producer's and user's classification accuracies varied across zones and cover types. Producer's accuracy is a measure of the percentage of the pixels in a land-cover class category that was correctly classified, while user's accuracy is a measure of the percentage of a land-cover class that was not misclassified as another class. Classification accuracy for zones 63 and 64 was constant between zones, but varied across cover types: deciduous forest had the highest producer's accuracy (86%), while pasture and hay had the highest user's accuracy (86.5%), and mixed forest had the lowest producer's accuracy (71%) and the lowest user's accuracy (73.8%; U.S. Department of Commerce 2007a;b). Accuracy of data for zone 65 varied across cover types: cultivated lands had the highest producer's accuracy (89%), while pasture and hay had the highest user's accuracy (97%), and pasture and hay, grassland, and deciduous forest all had the same and lowest producer's accuracy (80%), while grassland and mixed forest had the same and lowest user's accuracy (67%; U.S. Department of Commerce 2006).

We quantified landscape characteristics of C-CAP cover types using program Fragstats Version 3.3 (McGarigal et al. 2002, Marks et al. 2010). We assessed landscape characteristics at the landscape-level; Fragstats considered all 6 cover types (i.e., cultivated land, pasture and hay, grassland, deciduous forest, evergreen forest, and mixed forest) collectively when calculating the following 3 landscape-level metrics. Previous research indicated the importance of several configuration metrics that represent important habitat for eastern wild turkeys: contrast-weighted edge density (CWED; Glennon and Porter 1999, Fleming 2003), mean shape index (MSI; Fleming 2003) and interspersion and juxtaposition (IJI; Glennon and Porter 1999). We calculated

CWED under the assumption that edges created between forest and open cover types are either abrupt or the shrub transition between forests and open lands. Thus we assigned maximum contrast between forest and open types and no contrast between forest types and between open types (Glennon and Porter 1999, Fleming 2003). Therefore, CWED represented either the abrupt edges or the shrub transition zone. MSI measured the complexity of land-cover patch shapes on the landscape. Low values of MSI indicated that cover types on the landscape are comprised of simple, smooth configurations (e.g., a pasture) along which predators could more easily locate nests, while high values suggested more complex configurations (e.g., forest bordering a riparian corridor), thus making the location of nest more difficult for predators to find while traveling along edges (Fleming 2003). IJI measured how much the cover types are intermixed; a high IJI value indicates high proximity of patches to patches of as many other class types as possible. We think that intermediate values of interspersion and juxtaposition of cover types are important to turkeys because more patches of multiple cover types are highly accessible when configured in an interspersed pattern, but at a higher level of interspersion the landscape habitat may be too fragmented degrading the habitat quality and potentially resulting in a number of demographic consequences (e.g. increased nest predation, decreased survival).

We used a moving window approach to quantify CWED, MSI, and IJI across NYS at 5 scales (i.e., radii; extents): 1 km, 5 km, 10 km, 15 km, and 20 km. We chose these scales because they approximate the scales at which different processes occur. The smallest scale (1 km) approximates the size of a wild turkey's home range depending on the season and age and sex (Porter 1977). Nest predation risk is related to habitat features within a 5 km radius of the nest (5 km; Fleming 2003). Dispersal is facilitated by local (5 km) habitat connectivity, while barriers to dispersal are also likely operating at larger scales (10 km, 15 km, and 20km; (Fleming and Porter

2007a). We used zonal statistics in ArcGIS Version 10.2 (ESRI 2014) to calculate the mean of each metric across each township.

We obtained data for total rainfall and minimum temperature during May and June for every study year from Oregon State University's Parameter-elevation Regressions on Independent Slopes Model (PRISM) climate mapping system (PRISM Climate Group 2012). We calculated total May and June rainfall and average minimum temperature for May and June for each township using zonal statistics in ArcGIS Version 9.2 to average the raster values within each township.

Hypotheses

We explored hypotheses that included weather only, habitat only, both weather and habitat, and interactions between weather and habitat (Table 3-1). We evaluated the idea that there are ideal intermediate values of some weather and habitat variables by inclusion of quadratic terms in some weather only, habitat only, and then both weather and habitat models. The most complex model had interactions between weather and habitat in addition to quadratic relationships.

Table 3-1. Model set for each of state-wide, southern and northern New York of fixed effects only. The random effects were the same across all models within the set.

Model Group	Model
Weather only	Y [a] + JR [b] + JT [c]
	Y + MR [d] + JR
	Y + MR + JR + MT [e] + JT
	Y + MR + JR + MT + JT + (MR × MT) + (JR × JT)
	Y + JR + JT + JT^2 [f]
	Y + MR + JR + MT + JT + MT^2 [g] + JT^2
Habitat only	Y + MSI [h]
	Y + CWED [i]
	Y + IJI [j]
	Y + CWED + IJI
	Y + IJI + MSI
	Y + CWED + MSI
	Y + CWED + IJI + MSI
	Y + CWED + $CWED^2$ [k] + IJI + IJI^2 [l] + MSI + MSI^2 [m]

Table 3-1 (cont'd)

Weather and habitat	$Y + JR + JT + CWED + IJI + MSI$
	$Y + MR + JR + CWED + IJI + MSI$
	$Y + MR + JR + MT + JT + CWED + IJI + MSI$
	$Y + MR + JR + MT + JT + (MR \times MT) + (JR \times JT) + CWED + IJI + MSI$
	$Y + JR + JT + JT^2 + CWED + IJI + MSI$
	$Y + MR + JR + MT + JT + MT^2 + JT^2 + CWED + IJI + MSI$
Weather and quadratic relationships between habitat and productivity	$Y + JR + JT + CWED + CWED^2 + IJI + IJI^2 + MSI + MSI^2$
	$Y + MR + JR + CWED + CWED^2 + IJI + IJI^2 + MSI + MSI^2$
	$Y + MR + JR + MT + JT + CWED + CWED^2 + IJI + IJI^2 + MSI + MSI^2$
	$Y + MR + JR + MT + JT + (MR \times MT) + (JR \times JT) + CWED + CWED^2 + IJI + IJI^2 + MSI + MSI^2$
	$Y + JR + JT + JT^2 + CWED + CWED^2 + IJI + IJI^2 + MSI + MSI^2$
	$Y + MR + JR + MT + JT + MT^2 + JT^2 + CWED + CWED^2 + IJI + IJI^2 + MSI + MSI^2$
Weather, habitat and interactions between weather and habitat	$Y + MR + JR + CWED + IJI + MSI + (MR \times CWED) + (JR \times CWED) + (MR \times IJI) + (JR \times IJI) + (MR \times MSI) + (JR \times MSI)$

Y [a]: Year

JR [b]: Total June Rain

JT [c]: June Minimum Temperature

MR [d]: Total May Rain

MT [e]: May Minimum Temperature

Table 3-1 (cont'd)

JT^2[f]:	Quadratic relationship with June Minimum Temperature
MT^2[g]:	Quadratic relationship with May Minimum Temperature
MSI[h]:	Mean shape index at the 20 km-radius scale
CWED[i]:	Contrast-weighted edge density at the 5 km-radius scale
IJI[j]:	Interspersion/juxtaposition at the 1 km-radius scale
$CWED^2$[k]:	Quadratic relationship with contrast-weighted edge density at the 5 km-radius scale
IJI^2[l]:	Quadratic relationship with interspersion/juxtaposition at the 1 km-radius scale
MSI^2[m]:	Quadratic relationship with mean shape index at the 20 km-radius scale

Weather – We predicted that productivity was largely driven by spring weather and tested several hypotheses. We hypothesized that May and June rainfall and minimum temperatures affected productivity in different ways, looking at combinations of the following. We predicted that May rainfall and June rainfall decreased productivity while May minimum temperature and June minimum temperature increased with productivity or productivity was maximized at intermediate levels of temperature (i.e., had a hump-shaped quadratic relationship). We also predicted interaction relationships between concurrent rainfall and minimum temperature.

Habitat – We predicted that productivity was largely driven by habitat and tested several hypotheses that included 1, 2, or all 3 of the following landscape configuration metrics. We predicted that as MSI (complexity of the 6 cover types patch shapes) increased, productivity increased; as IJI of the 6 cover types increased, productivity increased, and as CWED (density of abrupt edges: between open and forested types) increased, productivity increased.

Statistical Modeling

We assessed the fit of models relating linear and nonlinear contributions of habitat configuration and weather to brood flock counts collected at the township level from 1996–2009. We evaluated these models with 3 separate analyses: one analysis that used the collective data set across the entire state, and 2 analyses examined the northern and southern portions of the state. We stratified these data into northern and southern regions because there is evidence that observed brood flocks vary regionally, in that counts are smaller and more stable in northern regions and fluctuate markedly over time in southern regions (Fig 3-1B).

We fit mixed-effects negative binomial regression models to habitat and weather covariates using brood flock counts as a response variable. We used the negative binomial distribution because brood flock count data were overdispersed (variance > mean; Hilbe 2011).

We fit models using the package glmmADMB version 0.7.7 (Skaug et al. 2013) in program R version 2.15.3 (R Development Core Team 2010). We fit models in 4 stages to first select the variance-mean relationship that is associated with the negative-binomial distribution, and then to identify the appropriate random effects structure, thirdly to identify the scale at which brood flocks were most sensitive to our configuration covariates, and finally to evaluate hypotheses about how habitat and weather affect productivity.

The glmmADMB package provides 4 ways to parameterize the variance-mean relationships for negative binomial regression: 1) linear relationship between variance and mean (variance(brood flocks) = $\phi\mu$; ϕ is a scaling parameter); 2) linear relationship between variance and mean with zero-inflation; 3) quadratic relationship between variance and mean (μ) (variance(brood flocks) = $\mu(1 + \mu/\kappa)$), and 4) quadratic relationship between variance and mean with zero-inflation. We used Akaike's Information Criterion (AIC; Burnham and Anderson 2002) to select the most parsimonious variance-mean parameterization using the global fixed-effects model with the state-wide dataset.

Productivity at a given township likely fluctuates through time, and productivity from a given year is likely to be more similar in adjacent townships due to factors not included as covariates, which suggests the need to consider different random effects structures which account for variability across time and/or space that the covariates (i.e., fixed effects) do not. We evaluated 4 random effects structures using the global fixed-effects model with the state-wide dataset and the top variance-mean parameterization (see above). The first random effects structure was the most parameterized of the 4 structures (eq 3-1): a spatio-temporal random intercepts model with a random slope for year within township. The random intercepts allow for random effects for township and year (Irwin et al. 2013). This treated both township and year as block random effects, and allowed for correlated brood flock counts across time at a given township or across all townships in a given year (Bolker et al. 2013, Irwin et al. 2013). We used a random slope effect to allow strength of linear time trends in brood flock data to vary spatially among townships (Irwin et al. 2013). The second random effects structure (eq 3-2) was a spatial random intercepts model which allowed for random effects for township. This effectively treated township as a block random effect, and allowed for correlated brood flock counts across time at a given township (Bolker et al. 2013). The third random effects structure (eq 3-3) was a temporal random intercepts model which allowed for random effects for year. This effectively treated year as a block random effect, and allowed for correlated brood flock counts across township at a given year (Bolker et al. 2013). The fourth random effects structure (eq 3-4) was a random slope model to allow strength of linear time trends in brood flock data to vary spatially among townships. We used AIC to identify the appropriate random effects structure, and this structure was applied to all subsequent models.

Furthermore, we used a log link to model the expected value of brood flock counts as a function of hypothesized covariates:

$$\ln(\mu_{\mathrm{ij}}) = \beta_0 + a_i + b_j + t_i \mathrm{Year}_{\mathrm{j}} + \Sigma^{G}{}_{g=1} \beta_g X_{g\mathrm{ij}}, \quad \text{eq 3-1}$$

$$\ln(\mu_{\mathrm{ij}}) = \beta_0 + a_i + \Sigma^{G}{}_{g=1} \beta_g X_{g\mathrm{ij}}, \quad \text{eq 3-2}$$

$$\ln(\mu_{\mathrm{ij}}) = \beta_0 + b_j + \Sigma^{G}{}_{g=1} \beta_g X_{g\mathrm{ij}}, \quad \text{eq 3-3}$$

$$\ln(\mu_{\mathrm{ij}}) = \beta_0 + t_i \mathrm{Year}_{\mathrm{j}} + \Sigma^{G}{}_{g=1} \beta_g X_{g\mathrm{ij}}, \quad \text{eq 3-4}$$

where β_0 is the intercept, a_i is the random intercept for township i (constant across time), b_j is the random intercept for year j (constant across townships), t_i is the random slope for the linear time trend at township i, and β_g is the effect of covariate X_g on productivity, where G is the total number of covariates (includes fixed effect average time trend across all townships). The random intercepts and slope for all mixed-effects models were assumed to be independent and identically-distributed normal random effects (e.g., $a_i \sim N(0,\sigma^2_a$; Irwin et al. 2013).

Finally, we identified the scale at which productivity was most sensitive to CWED, MSI, and IJI. We fit each univariate, scale-metric permutation (15 models) and used AIC to choose the best model. If the choice of scale was clear for one or more of the 3 metrics but unclear for the other(s), we again fit each scale-metric permutation for the metrics that were unclear, but with the additional metric(s) for which the scale had been clearly chosen by AIC from the first scale-examination exercise. For example, if the 15 km scale for CWED was the most parsimonious among the 5 scales at which CWED was measured, but there were competing AIC scores for the different scales at which MSI was measured, we would fit bivariate models, again each with a different scale for MSI, but with the addition of CWED measured at the 15 km scale (5 models). Again we used AIC to choose the best model.

We developed an a priori set of 27 models representing our ecological hypotheses using different combinations of habitat and weather covariates (Table 3-1). Each model included year as a fixed effect.

We treated covariates in the following manner. We standardized the covariates by subtracting the mean from each data point and dividing by the standard deviation. We calculated Pearson's product-moment correlation coefficients to evaluate pair-wise correlations between habitat covariates and between weather covariates using program R. We used a $\rho > 0.7$ as the threshold for excluding correlated covariates from a regression model because evidence suggests pairwise correlations of regression covariates does not affect standard error estimates unless correlations are approximately > 0.8 (Fox 2008). We did not find correlations between covariates that were to be included in the same models in the a priori model set.

For the most parsimonious models, we evaluated model assumptions and fit using root mean squared-error (RMSE) and Anscombe residuals for diagnostic plots (Hilbe 2011, Irwin et al. 2013). We reported the most parsimonious model (smallest AIC) from each of the 3 analyses (i.e., statewide, southern NYS, and northern NYS). When the 95% confidence intervals (CI) of the coefficient estimates did not overlap 0, the relationships between ecological variables and productivity were considered statistically significant.

RESULTS

The state of New York had brood flock data for 839 townships, across 14 years (n = 4,013). Regionally, brood flocks occurred at 656 townships in southern New York (n = 3,086) and 165 townships in northern New York (n = 868). The first 3 stages of our modeling approach identified the following: 1) a quadratic relationship between the variance-mean is optimal (Table 3-2), 2) the most complex random effects structure (eq. 1) provides the best fit (Table 3-3), and 3) the scale at which brood flocks are most sensitive to habitat covariates varies by metric. In general, the 20 km scale for MSI and 1 km scale for IJI were consistently present in our top models (Table 3-4). The scale for CWED was less clear so we chose the 5 km scale, which aligns with the scale at which landscape configuration affects nest success (Fleming 2003) and dispersal (Fleming and Porter 2007a).

Table 3-2. Model set for the error structure for the entire state of New York during 1996−2009. Each of the models included all the random effects and the entire set of fixed effects (with the landscape variables measured at the 5 km scale). K is the number of parameters estimated, and w is the weight of the model.

Error structure	ΔAIC	K	w
quadratic[a]	0	25	0.729
quadratic with zero inflation	2	26	0.271
linear with zero inflation	48.5	26	<0.001
linear[b]	49.6	25	<0.001

[a] $\mathrm{Var(harvest)} = \mu(1+ \mu/\kappa)$

[b] $\mathrm{Var(harvest)} = \phi\mu$

Table 3-3. Model set for the random effects structure for the entire state of New York during 1996−2009. Each of the models included the error structure previously chosen by AIC and the entire set of fixed effects (with the landscape variables measured at the 5 km scale). K is the number of parameters estimated, and w is the weight of the model.

Model	ΔAIC	K	w
$\ln(\mu_{ij}) = \beta_0{}^{a} + a_i{}^{b} + b_j{}^{c} + t_i{}^{d}\,\mathrm{Year}_j$ + fixed effects [e]	0	25	1
$\ln(\mu_{ij}) = \beta_0 + t_i\mathrm{Year}_j$ + fixed effects	45	24	<0.001
$\ln(\mu_{ij}) = \beta_0 + a_i$ + fixed effects	55.5	23	<0.001
$\ln(\mu_{ij}) = \beta_0 + b_j$ + fixed effects	380.2	23	<0.001

β_0 [a]: intercept

a_i [b] is the random intercept for township i (constant across time),

b_j [c] is the random intercept for year j (constant across townships),

t_i [d] is the random slope for the linear time trend at township i, and

fixed effects [e]: $\Sigma^{G}_{g=1} \beta_g X_{gij}$ β_g is the effect of covariate X_g on productivity, where G is the total number of covariates (includes fixed effect average time trend across all townships)

Table 3-4. Model sets for the landscape scale structures for the entire state. Each of the models included all the random effects and the error structure previously chosen by AIC. K is the number of parameters estimated, and w is the weight of the model.

Model			ΔAIC	K	w
	Mean Shape Index (MSI)	20 km	0	7	0.5471
		15 km	2.3	7	0.1715
		1 km	3	7	0.1233
		10 km	3.6	7	0.0904
		5 km	4.2	7	0.0677
	Interspersion and Juxtaposition (IJI)	1 km	0	7	0.218
		20 km	0.2	7	0.197
		15 km	0.2	7	0.195
		5 km	0.2	7	0.195
		10 km	0.2	7	0.194
	Contrast-Weighted Edge Density (CWED)	1 km	0	7	0.216
		5 km	0	7	0.214
		10 km	0.2	7	0.198
		20 km	0.3	7	0.19
		15 km	0.3	7	0.182
Mean Shape Index (MSI) 20 km	Interspersion and Juxtaposition (IJI)	1 km	0	8	0.425
		5 km	2.2	8	0.144
		10 km	2.2	8	0.144
		20 km	2.2	8	0.144
		15 km	2.2	8	0.143
Mean Shape Index (MSI) 20 km	Contrast-Weighted Edge Density (CWED)	1 km	0	8	0.243
		5 km	0	8	0.243
		10 km	0.3	8	0.209
		15 km	0.8	8	0.165
		20 km	1.1	8	0.14

We found statewide productivity to be best explained by year, May rainfall and temperature, June rainfall and temperature, and each of the 3 habitat covariates along with their respective quadratics (Table 3-5), but no interaction terms were included. IJI within 1 km had a quadratic relationship with productivity (IJI + IJI^2; $\beta = -0.014$ 95% CI = -0.067 to 0.039, P = 0.611, $\beta^2 = -0.037$, 95% CI = -0.062 to -0.012, P = 0.004), although the linear term was not significant. When examining the effect that state-wide values of IJI had on state-wide brood flock numbers (Fig 3-2A), productivity increases with increasing IJI, and then values of IJI near 60 maximize productivity. We did not have confidence in the coefficient estimates of the remaining covariates in the top model (i.e., the confidence intervals overlapped zero). In the 2 additional competing models (i.e., within 2 AIC units), the coefficient estimates are all of the same strength and direction of their counterparts from the top model.

Table 3-5. Partial model sets for the ecological structures for the entire, the southern, and the northern portions of New York State. Each of the models included all the random effects and the error structure previously chosen by AIC. Only models within 6 AIC of the top are included. K is the number of parameters estimated, and w is the weight of the model.

	Model	ΔAIC	K	w
State-wide	Y [a] + MR [b] + JR [c] + MT [d] + JT [e] + CWED [f] + $CWED^2$ [g] + IJI [h] + IJI^2 [i] + MSI [j] + MSI^2 [k]	0	16	0.264
	Y + MR + JR + MT + JT + MT^2 [l] + JT^2 [m] + CWED + $CWED^2$ + IJI + IJI^2 + MSI + MSI^2	0.8	18	0.179
	Y + JR + JT + CWED + $CWED^2$ + IJI + IJI^2 + MSI + MSI^2	1.3	14	0.139
	Y + CWED + $CWED^2$ + IJI + IJI^2 + MSI + MSI^2	2.2	12	0.087
	Y + MR + JR + CWED + $CWED^2$ + IJI + IJI^2 + MSI + MSI^2	2.3	14	0.085
	Y + MR + JR + MT + JT + (MR × MT) + (JR × JT) + CWED + $CWED^2$ + IJI + IJI^2 + MSI + MSI^2	3.1	18	0.056
	Y + JR + JT + JT^2 + CWED + $CWED^2$ + IJI + IJI^2 + MSI + MSI^2	3.3	15	0.052
	Y + MR + JR + MT + JT	4.7	10	0.025
	Y + MR + JR + MT + JT + MT^2 + JT^2	5.5	12	0.017

Table 3-5 (cont'd)

Southern	Y + JR + JT + CWED + CWED^2 + IJI + IJI^2 + MSI + MSI^2	0	14	0.168
	Y + MR + JR + MT + JT + CWED + CWED^2 + IJI + IJI^2 + MSI + MSI^2	0	16	0.168
	Y + MR + JR + MT + JT + MT^2 + JT^2 + CWED + CWED^2 + IJI + IJI^2 + MSI + MSI^2	0.4	18	0.135
	Y + CWED + CWED^2 + IJI + IJI^2 + MSI + MSI^2	1.4	12	0.084
	Y + IJI + MSI	1.6	8	0.076
	Y + JR + JT + JT^2 + CWED + CWED^2 + IJI + IJI^2 + MSI + MSI^2	1.7	15	0.073
	Y + MR + JR + MT + JT + (MR × MT) + (JR × JT) + CWED + CWED^2 + IJI + IJI^2 + MSI + MSI^2	2.3	18	0.053
	Y + MR + JR + MT + JT + CWED + IJI + MSI	2.9	13	0.039
	Y + JR + JT + CWED + IJI + MSI	3	11	0.038
	Y + MR + JR + MT + JT + MT^2 + JT^2 + CWED + IJI + MSI	3	15	0.037
	Y + CWED + IJI + MSI	3.3	9	0.033
	Y + MR + JR + CWED + CWED^2 + IJI + IJI^2 + MSI + MSI^2	4.2	14	0.021
	Y + JR + JT + JT^2 + CWED + IJI + MSI	5	12	0.014
	Y + MR + JR + MT + JT	5.3	10	0.012
	Y + MR + JR + MT + JT + MT^2 + JT^2	5.8	12	0.009
	Y + MR + JR + CWED + IJI + MSI	5.8	11	0.009

Table 3-5 (cont'd)

Northern	Y + IJI	0	7	0.428
	Y + IJI + MSI	1.8	8	0.176
	Y + CWED + IJI	2	8	0.157
	Y + CWED + IJI + MSI	3.8	9	0.065
	Y + CWED	5.3	7	0.03
	Y + MSI	5.9	7	0.023

Y [a]: Year

MR [b]: Total May Rain

JR [c]: Total June Rain

MT [d]: May Minimum Temperature

JT [e]: June Minimum Temperature

CWED [f]: Contrast-weighted edge density at the 5 km-radius scale

$CWED^2$ [g]: Quadratic relationship with contrast-weighted edge density at the 5 km-radius scale

IJI [h]: Interspersion/juxtaposition at the 1 km-radius scale

IJI^2 [i]: Quadratic relationship with interspersion/juxtaposition at the 1 km-radius scale

MSI [j]: Mean shape index at the 20 km-radius scale

MSI^2 [k]: Quadratic relationship with mean shape index at the 20 km-radius scale

MT^2 [l]: Quadratic relationship with May Minimum Temperature

JT^2 [m]: Quadratic relationship with June Minimum Temperature

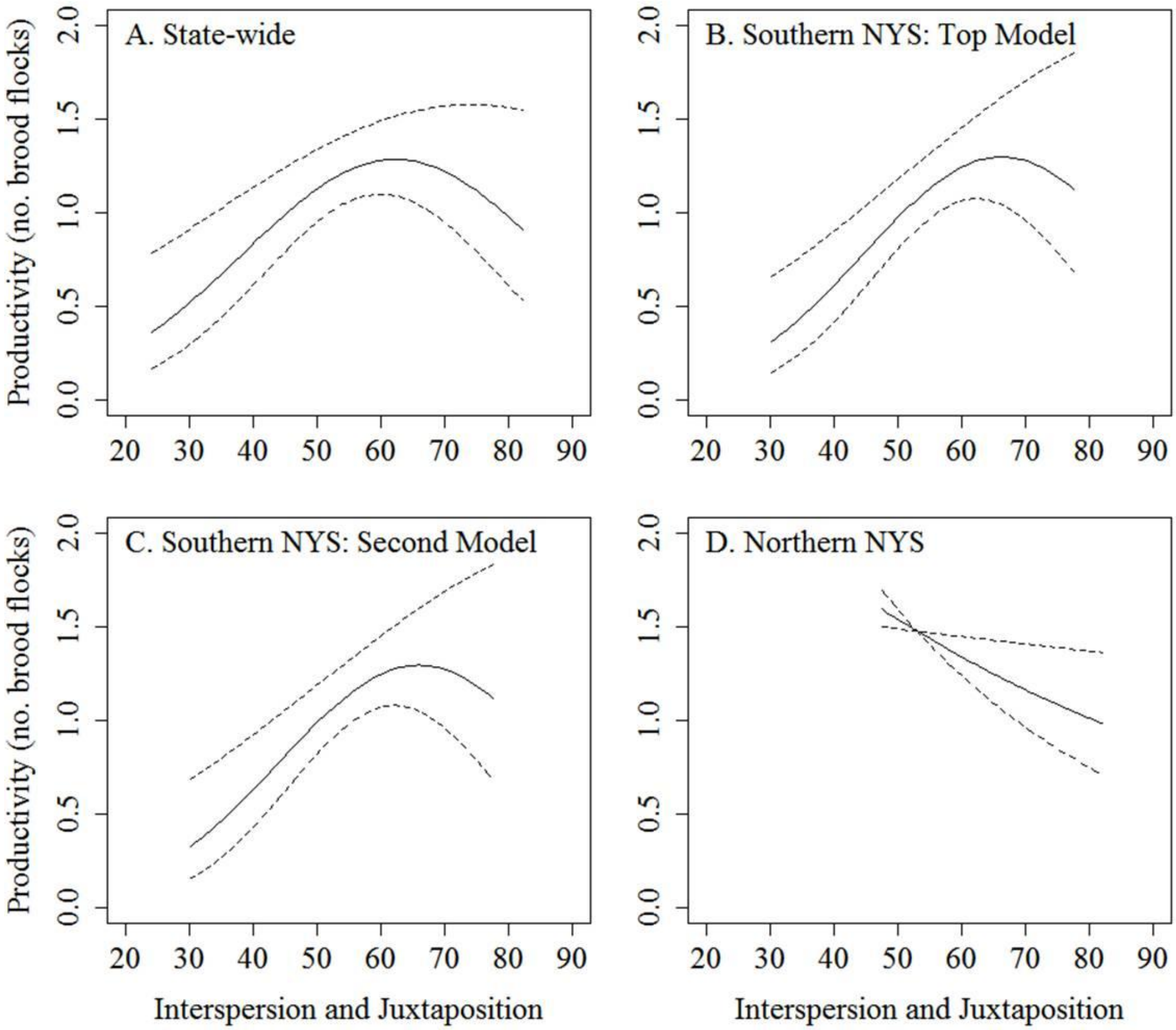

Figure 3-2. The relationships between interspersion/juxtaposition of cover types at the 1 km scale and township-level productivity were different state wide (A), and between southern (B and C) and northern (D) New York State (NYS) for years 1996−2009 (95% confidence intervals indicated by dashed lines). Increasing interspersion/juxtaposition state-wide and in the south had a quadratic relationship with values of IJI between 60 and 70 maximizing productivity. Increasing interspersion/juxtaposition in the northern region decreased productivity.

We found productivity in the southern region to be best explained by year, May rainfall and temperature, June rainfall and temperature, and each of the 3 habitat covariates along with their respective quadratics (Table 3-5), but no interaction terms were included. There were 2 top models (i.e., ΔAIC = 0) and 4 additional competing models (ΔAIC ≤ 2; Table 3-5). The first top model did not include May rainfall and temperature. The average minimum temperature in June (JT; $\beta = -0.056$, 95% CI = −0.11 to −0.002, $P = 0.039$; Fig 3-3A) and the MSI for habitat patches within 20 km (MSI; $\beta = -0.071$, 95% CI = −0.127 to −0.016, $P = 0.012$; Fig 3-4A) decreased productivity, while IJI within 1 km had a hump-shaped quadratic relationship with productivity (IJI + IJI^2; $\beta = 0.035$, 95% CI = −0.032 to 0.102, $P = 0.303$, $\beta^2 = -0.042$, 95% CI = −0.073 to −0.01, $P = 0.009$), although the linear term was not significant. When examining the effect that IJI values in the southern region had on southern brood flock numbers (Fig 3-2B), productivity increases with increasing IJI, then the values of IJI between 60 and 70 maximize productivity, after which increasing IJI decreases productivity, although there is some uncertainty at values above the inflection. The other top model included all the same covariates as the first top model as well as May rainfall and temperature. The average minimum temperature in May (MT; $\beta = -0.076$, 95% CI = −0.1501 to −0.002, $P = 0.044$; Fig 3-3B) and the MSI for habitat patches within 20 km (MSI; $\beta = -0.068$, 95% CI = −0.124 to −0.012, $P = 0.017$; Fig 3-4B) decreased productivity, while IJI within 1 km had a hump-shaped quadratic relationship with productivity (IJI + IJI^2; $\beta = 0.03$, 95% CI = −0.037 to 0.097, $P = 0.374$, $\beta^2 = -0.041$, 95% CI = −0.072 to −0.01, $P = 0.01$; Fig 3-2C), although the linear term was not significant. In the 4 competing models, the coefficient estimates are all of the same direction and of similar magnitude of their counterparts from the top model.

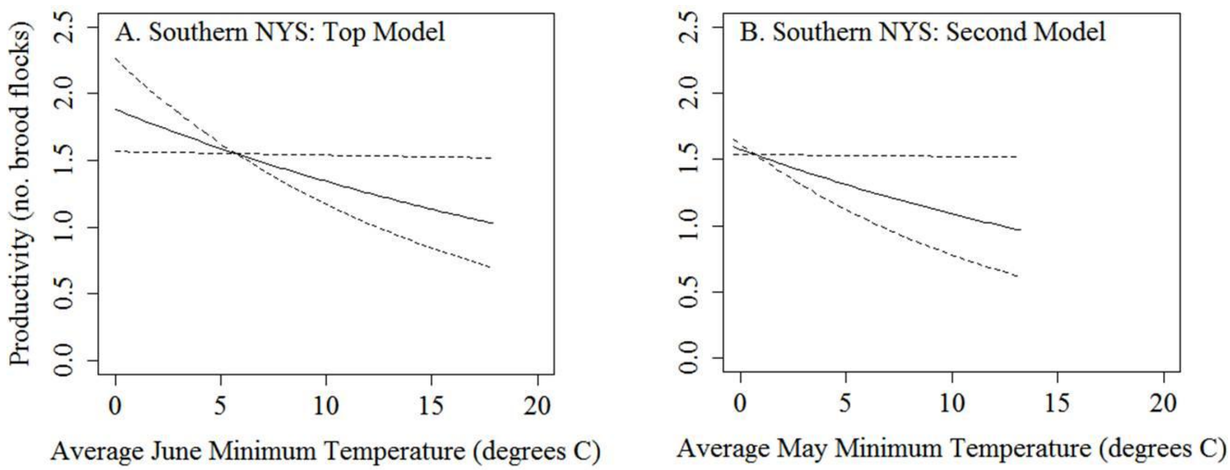

Figure 3-3. Average spring monthly minimum temperature effects on township-level productivity in the southern region of New York State (NYS) for years 1996−2009 (95% confidence intervals indicated by dashed lines). One top model (A) showed that increasing June minimum temperature decreased productivity, while the second top model (B) showed that increasing May minimum temperature decreased productivity.

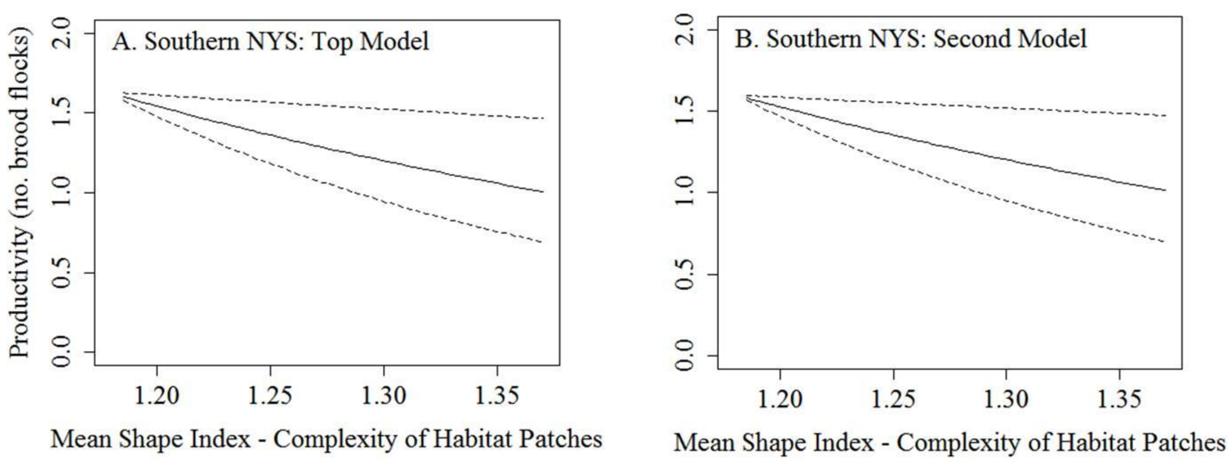

Figure 3-4. Mean shape index of habitat patches decreased township-level productivity in southern region of New York State (NYS) for years 1996−2009 (95% confidence intervals indicated by dashed lines). The strength and direction of the estimates are similar in the first top (A) and second top (B) model.

We found productivity in the northern region to be best explained by year and IJI (Table 3-5); IJI decreased productivity ($\beta = -0.1$, 95% CI = −0.173 to −0.019, $P = 0.014$; Fig 3-2D). In the 2 additional competing models, the coefficient estimates for IJI are also negative, and they are of similar magnitude.

Model performance was good; the models fit the data well. The fitted values from the top state-wide model (RMSE = 1.328), the southern region's simpler top model (RMSE = 1.354), the southern region's slightly more complex top model (RMSE = 1.352), and the northern region's top model (RMSE = 1.242) were all very close to their respective observed values. The average yearly difference between the observed brood flock counts and the fitted values from the models was small. The mean models fit the observed values less well with higher RMSE (i.e., state-wide RMSE = 1.632, southern region RMSE = 1.689, and northern region RMSE = 1.426).

DISCUSSION

Three important messages emerge from these analyses. First, the impact of habitat features on productivity in wild turkeys is scale-dependent, as evidenced by the metrics measured at one scale being chosen over the same metrics measured at other scales. While biologists have long recognized the importance of habitat, a full understanding of the drivers of productivity has not been possible because there has been little research investigating the influences of landscape-scale habitat and spring weather on productivity. Second, our assessment of the relative roles of habitat and weather suggests that over the long term, habitat may play a more important role than rainfall in successful brood production because of the lack of significant effect of rainfall. Habitat is the key over the long term if the periodicity of severe weather allows populations to recover. When habitat is very good, populations grow more. When severity is moderate, habitat mitigates some of the effect. Past research has demonstrated a strong relationship between spring rainfall and fall turkey populations, but our work suggests further research is needed to elucidate the relationship between rainfall and productivity because biologists cannot manage rainfall, but knowledge of its effects is useful for predicting future productivity. Further, findings here suggest temperature may be an important driver. There are regional differences in important drivers and differences in the effect of drivers on productivity, which points to the need to interpret drivers in the appropriate landscape context. Finally, our comparison of regions showed that more suitable areas of higher-quality habitat are also affected by weather and are marked by greater fluctuation in productivity. Thus, the forest-agricultural matrix environments of southern New York provide better habitat characteristics due to the larger variety of cover types, but show more pronounced variation in productivity than northern New York where forests are contiguous.

We were able to identify specific scales of landscape pattern to which productivity was responsive. Productivity was responsive to IJI at the 1 km scale, which aligns with the need for resources to be in close proximity of one another, accessible within normal daily movements. Increasing interspersion and juxtaposition in the south had a humped-shaped quadratic relationship (i.e., there are intermediate values of IJI that are most beneficial to productivity because interspersion of habitats provides accessibility, up to a certain point, beyond which the landscape is too fragmented to be good habitat). There are high proportions of non-forest land-cover types in the southern region, so the values of interspersion and juxtaposition in this region likely represent the intermixing of all 6 cover types of interest, which is good brood habitat, thereby increasing productivity (Lewis 1992, Wunz and Pack 1992, Glennon and Porter 1999, Fleming and Porter 2007a), while the highest interspersion of cover types decreases productivity. In all but one competing models for the southern region, IJI consistently had a quadratic relationship with productivity; while in the other model, IJI was associated with increasing productivity. In the north, the IJI values likely represent intermixing of forest types (e.g., evergreen and mixed in the Adirondacks and Tug Hill), and this type of structural heterogeneity likely is not what represents good brood habitat which may be an explanation for the negative relationship between IJI and productivity.

We found that in southern New York, productivity decreased with increasing complexity of habitat patch shapes within 20 km. In a previous study, mean shape index for patches within 5 km of a nest site had been found to increase nest success perhaps by decreasing the likelihood that a predator searching along a complex patch’s edge would find a nest (Fleming 2003). The seemingly disparate findings here are likely a result of the differing mechanisms operating on nest success and productivity. Simpler shapes may increase the ease with which broods access the habitat type for which they are searching (i.e., connectivity or permeability) because if the shape of a patch is too complex then other patch types may not be easily accessible. Additionally, complex shapes may not be important to broods as they are not susceptible to predation in the same manner as nests. There likely is also a scale disconnect, in that the impact on nest predation at 5 km does not scale up to 20 km. The complexity of all the patch shapes within 20 km of a brood likely does not impact broods in the same manner as the complexity of all the patch shapes within 5 km of a nest. Instead, complex-shaped patches may provide predator habitat and thus increase predator numbers thereby decreasing brood flock numbers The relationship also may reflect a process unrelated to ecology which is discussed below.

Our findings were counter to what we expected for the relationships between spring weather and productivity. We could not find a relationship demonstrating that May or June rainfall affected productivity. We did not find evidence for interactions between precipitation and habitat; the interaction terms were not in any of the top models. This suggests that the major driver supporting large-scale measures of productivity is habitat and may not depend on rainfall. These findings are similar to Fleming and Porter (2007b), in which they found no evidence for a relationship between spring weather and wild turkey populations across large regions (e.g., 126,000 km^2). They hypothesized that the large spatial scale and short time scale at which they had examined the relationship, weather played a much lesser role, and therefore was not detected. Brood counts continue to be conducted and as the data set grows and represents a longer time scale, the drivers should be re-evaluated.

Increasing May and June minimum temperature in the south contributed to decreased productivity. Porter and Gefell (1996) found that heating degree days (i.e., cold temperatures) in May and June were negatively associated with abundance, while heating degree days in March and April were positively associated with abundance, and both variables had to be included; they did not examine precipitation. We saw the opposite relationship with May and June temperature and productivity, but did not examine March and April temperatures. We had expected cool minimum temperatures to interact with rainfall to decrease poult survival and, therefore, decrease productivity. However, perhaps because rainfall did not affect productivity, cool minimum temperatures in May and June could not detrimentally affect productivity alone. Rather, warmer minimum temperatures affected the birds in a negative manner through a different mechanism. Perhaps trophic mismatch is occurring (Harrington et al. 1999, Visser and Both 2005, Both et al. 2009); maybe at higher spring temperatures, insects emerge sooner and are ill-timed for consumption by poults.

There is a need to recognize and account for regional differences in relationships and consider how different landscape metrics may perform differently or represent different landscape phenomena in different regions. The relationship between interspersion and juxtaposition of cover types at the 1 km scale and productivity was different between southern and northern New York State. Due to the strong north vs. south regional differences, the state-wide quadratic relationship with IJI likely is not useful to interpret.

Overall brood flock counts are higher and fluctuate more in the south than in the north. The lower numbers in the north are likely due to higher proportions of forested lands, especially evergreen forest, and lower proportions of open lands, which are important brood habitat (Gefell 1991). Perhaps higher spring minimum temperatures are driving the fluctuations in the south; both minimum May and June temperatures are lower in the north than the south, and increasing spring temperatures decreases productivity in the southern region whereas this relationship is not observed in the northern region. A variety of studies in the southern region of New York (Gefell 1991, Roberts et al. 1995, Roberts and Porter 1998a;b;2000) seem to indicate that the effects of spring weather on wild turkeys are more important on larger populations in high-quality habitats in the southern regions.

There are some constraints with interpreting the results. We had a relatively short time-series (1996-2009), and we did not have information on effort related to the collection of brood count data. Though this lack of effort data is typical of many states that collect productivity data for turkeys, we expect that variable effort will introduce noise in the data and affect our ability to explain relationships between productivity, habitat, and weather precisely (Gu and Swihart 2004, de Solla et al. 2005, Dickinson et al. 2010). May and June rainfall are specific examples of coefficients that were estimated imprecisely, and therefore cannot be said to affect productivity. However, because May rainfall has been successful in explaining nest success (Roberts and Porter 1998b) and fall harvest (Roberts and Porter 2000; Chapter 1), and June rainfall has been successful in explaining poult survival (Roberts and Porter 1998a) and fall harvest (Chapter 1), these drivers cannot be discounted, but rather should be included in future longer-term investigations.

The data collection methods themselves could have led to some ambiguous results. Generally, the northern region has fewer observations, in part due to lower road densities and fewer people reporting, which also contributes to the lower numbers of brood flocks in the north. Therefore, it is difficult to discern if some of the habitat relationships here (e.g., MSI) are biological or a result of data collection bias. An interpretation of MSI unrelated to ecology, but rather to data collection methodology, is that the complexity of patch shape is affecting not productivity, but the likelihood that brood flocks are seen and counted (Bart et al. 1995). The counts are done opportunistically in accessible places: along roads, and roads are generally simply-shaped, either running along the edges of the simplest patches or bisecting complex patches. However, because our models fit well, they are good at predicting productivity. Furthermore, perhaps a larger suite of variables that represent eastern wild turkey habitat, measured at different scales, would be more comprehensive and present a more complete picture. Future studies may include landscape composition more explicitly (i.e., test cover-type proportions for effects on productivity) in addition to our method of inclusion (i.e., measure configuration of the cover-types of interest). Future studies may also wish to include multiple sources of land-cover and land-use data, although little change can be seen using metrics calculated at large scales (e.g., 125 km^2; A. C. Bowling, Michigan State University, unpublished data).

The take-home messages from this study are multifold. Habitat configuration is a major driver of productivity, and it must be considered at multiple scales. Habitat configuration affects nest success (Fleming 2003), dispersal (Backs and Eisfelder 1990, Fleming and Porter 2007a), and fall harvest (Glennon and Porter 1999; Chapter 1), and now we have evidence that it also affects productivity. Spring weather did not have the anticipated relationship with productivity; we found that spring minimum temperatures decrease productivity in the southern region. We found regional differences in the drivers of productivity and in the levels and fluctuations across time in productivity. There may be other drivers of productivity as indicated by their inclusion in top-ranked models, and incorporating effort information may allow the importance of other drivers, like spring rainfall, to emerge. The general decline in recent productivity parallels the general decline in recent spring and fall harvest, and productivity data could be used to assess population changes.

EPILOGUE

Wild turkey populations have been restored to their historic range and into vegetation communities previously thought to be uninhabitable. Restoration was successful due to efforts from conservation organizations, state management agencies, and university researchers. Successful restoration efforts had produced exponentially-growing wild turkey populations, but in recent years wild turkey populations across North America have demonstrated different trends. Wild turkey populations may be declining or stabilizing across their range. Populations in New York State are experiencing similar trends; fall harvest, spring harvest, and productivity have all been declining. These declines have drawn questions concerning the large-scale ecological drivers of populations and subsequent harvest and how might managers reevaluate harvest regulations for declining populations. The goal of this study was not to explicitly quantify habitat quality decline, although some work (A. C. Bowling, unpublished data) shows that change is not detectable at the township-level across the spatial extent, and over the time period, of our study.

Habitat and weather are known to affect productivity and population size through reproductive success and survival. High spring rainfall had been previously identified as causing decreased nest success and poult survival and, due to the close tie between nest success and fall population size, predicted fall harvest. It had also been previously shown that winter severity decreased survival and body condition, but was mediated by agriculture food sources. I investigated these potential ecological drivers, especially weather, at much larger spatial extents than had been previously investigated. I was able to show interactions between regional habitat quality differences and weather and their effects on fall and spring population size at multiple large-scales. I was also able to identify the major large-scale drivers of productivity, which had not been previously investigated.

I found that the drivers of population size and subsequent harvest and productivity are context specific and, therefore, show that landscape-scale, township-level habitat and weather interact at a large spatial scale: across climate-ecozones within the 126,000 km^2 state of New York. Weather tends to be a driver in regions where high-quality habitat supports large populations. In regions that are of lower-quality habitat where resources are sparse, populations are small and therefore the small numbers demonstrate smaller fluctations and total population size is less affected by weather. In the forest-agriculture landscapes, May and June rainfall decreased fall populations and winter severity decreased spring populations. While in lower-quality highly-forested landscapes that experience consistently severe winters, weather does not affect fall or spring populations. At a smaller scale (i.e., within one climate-ecozone), in a high-quality forest-agriculture landscape, the detrimental effects of spring rainfall on fall populations are buffered by the availability of habitat while the detrimental effects of winter severity on spring populations are exacerbated by the detrimental effects of illegal harvest opportunities in open vegetation types. Productivity showed no apparent relationship with rainfall, but increasing spring temperature decreased productivity in the high-quality forest-agriculture landscape. However, there was no relationship between weather and productivity in the low-quality habitat of highly-forested landscapes.

My findings are relevant to eastern wild turkey populations of the Great Lakes states and Northeast US. There are varying degrees of forest and agriculture across these northern landscapes, and the climate at these latitudes is cool with varying degrees of seasonal moisture. Regional examination of the ecological drivers can reveal the interaction between the effects of habitat and weather on northern latitude eastern wild turkey populations.

The use of land-cover and land use data sets have their advantages and their limitations. I was able to make use of their many advantages. The data sets are very large (i.e., spanning all of the United States) and are released fairly frequently (i.e., nearly every 4 years) facilitating the comparison across many study areas. These data are at a resolution (30 m^2) appropriate for addressing many population-level questions. However, detailed information concerning forest age and successional stage is not available. Understory structure and composition in forests are unknown. It is unknown which crops are grown and how they are harvested in the culivated lands.

Natural resource managers have multiple management tools at their disposal. Harvest management and habitat management are the two which are available for managing wild turkey populations, and harvest management is feasible and recommended to implement at large spatial scales. I was able to inform managers of the relative regional fall harvest potential of populations according to the important ecological drivers of mean harvest and harvest variability. Managers can use this information to facilitate decisions regarding modification of spatially-varying harvest regulations. Current fall harvest regulations comprise 7 zones which vary in season length from 0 days to 7 weeks and in bag limit from 0 – 2 birds. The number of different zones can be reduced to a maximum of 3 according to the relative regional harvest potential (APPENDIX D).

I also showed no evidence of a negative relationship between fall harvest and spring populations available for harvest. Knowledge of this lack of relationship is important for managers when evaluating the legitimacy of multiple harvest seasons. Since this study is correlative, however, the only way determine a causal (or lack of evidence for) relationship between fall harvest and spring populations is to close fall seasons and montitor spring populations using a controlled experiment. Nevertheless, fall harvest rate is low, evidenced by the low numbers that are reported. Current spring regulations comprise 1 zone north of the Bronx-Westchester County boundary; the season lasts 4 weeks, and hunters have a bag limit of 2 bearded birds. These regulations are not under review, but if they come under review in the future, knowledge of the drivers and population levels can inform decisions.

APPENDICES

APPENDIX A. PRODUCER'S AND USER'S ACCURACY OF LAND COVER AND LAND USE DATA IN NEW YORK STATE.

Table A-1. Producer's and user's accuracy of land cover and land use data used to quantify landscape composition and configuration effects on fall harvest of wild turkeys in New York during 1984-2009. Producer's accuracy is a measure of the percentage of a land-cover class that was excluded from the appropriate classification, while user's accuracy is a measure of the percentage of a land-cover class that was misclassified as another class (inclusion).Values are percentages.

	NLCD and C-CAP LCLU data accuracy							
	1992		1996		2001 and 2006; US Coast zones 63 and 64		2001 and 2006; US Coast zone 65	
Class type	Producer's	User's	Producer's	User's	Producer's	User's	Producer's	User's
Cultivated lands	52	57	89	80	82	76.5	89	80
Pasture and Hay	47	41	80	97	76	86.5	80	97
Grassland	NA	NA	80	67	76	68.6	80	67
Deciduous forest	80	58	80	92	86	78.7	80	92
Evergreen forest	34	84	85	94	80	83.3	85	94
Mixed forest	67	44	86	67	71	73.8	86	67

APPENDIX B. FULL MODEL SELECTION TABLES AND COEFFICIENT ESTIMATES FROM THE TOP MODELS FOR FALL HARVEST IN THE 7 CLIMATE-ECOZONES IN NEW YORK STATE FROM 1984–2009.

Table B-1. Model set for analysis of drivers of fall harvest of wild turkeys in southwest New York during 1984-2009. Models below are for fixed effects only. Each of the models included all the random effects and the error structure previously chosen by AIC. K is the number of parameters.

Model name	ΔAIC	K
Y [a] + JR [b] + LLCom [c] + LLCom^2 [d] + LLCon [e] + LLCon^2 [f] + CLCon [g]	0	34
Y + MR [h] + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	1.5	35
Y + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	4.6	33
Y + MR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	6.3	34
Y + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (JR × LLCon) + (JR × CLCon)	6.3	46
Y + JR + LLCom + LLCon + CLCon	12.4	25
Y + MR + JR + LLCom + LLCon + CLCon	13.9	26
Y + LLCom + LLCon + CLCon	16.2	24
Y + MR + LLCom + LLCon + CLCon	17.8	25
Y + MR + JR + LLCom + LLCom^2 + (MR × LLCom) + (JR × LLCom)	17.9	32
Y + JR + LLCom + LLCom^2	18	19
Y + JR + LLGCom [i] + LLGCom^2 [j] + LLCon + LLCon^2 + CLCon	19.4	24
Y + JR + LLCom + LLCom^2 + (JR × LLCom)	19.7	25
Y + MR + JR + LLCom + LLCom^2	19.7	20
Y + JR + LLCom + LLCon + CLCon + (JR × LLCon) + (JR × CLCon)	19.8	37

Table B-1 (cont'd)

Y + MR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLCon) + (MR × CLCon)	20.5	46
Y + MR + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon	21	25
Y + LLCom + $LLCom^2$	21.5	18
Y + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon	21.6	23
Y + MR + JR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLCon) + (MR × CLCon) + (JR × LLCon) + (JR × CLCon)	22.5	59
Y + MR + LLCom + $LLCom^2$ + (MR × LLCom)	22.7	25
Y + MR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon	23.2	24
Y + MR + LLCom + $LLCom^2$	23.3	19
Y + JR + LLGCom + LLCon + CLCon	26.3	20
Y + MR + JR + LLGCom + LLCon + CLCon	27.8	21
Y + LLGCom + LLCon + CLCon	28	19
Y + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	28.5	37
Y + MR + LLGCom + LLCon + CLCon	29.6	20
Y + MR + LLCom + LLCon + CLCon + (MR × LLCon) + (MR × CLCon)	32.4	37
Y + MR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon)	32.6	37
Y + MR + JR + LLCom + LLCon + CLCon + (MR × LLCon) + (MR × CLCon) + (JR × LLCon) + (JR × CLCon)	36.5	50
Y + JR + LLGCom + LLCon + CLCon + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	36.5	33
Y + MR + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon)	36.9	51
Y + MR + LLGCom + LLCon + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon)	37.8	33
Y + MR + JR + LLGCom + LLCon + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	43.7	47
Y + JR + LLCom	47.2	13

Table B-1 (cont'd)

Y + JR + LLCom + (JR × LLCom)	47.3	19
Y + MR + JR + LLCom + (MR × LLCom) + (JR × LLCom)	47.5	26
Y + JR + LLCon + LLCon^2	48.5	13
Y + LLCon + LLCon^2	49.1	12
Y + MR + JR + LLCom	49.2	14
Y + LLCom	50	12
Y + MR + JR + LLCon + LLCon^2	50.2	14
Y + MR + LLCon + LLCon^2	50.9	13
Y + MR + LLCom + (MR × LLCom)	52	19
Y + MR + LLCom	52	13
Y + MR + LLCon + LLCon^2 + (MR × LLCon)	52.7	16
Y + JR + LLCon + LLCon^2 + (JR × LLCon)	53.8	16
Y + MR + JR + LLCon + LLCon^2 + (MR × LLCon)	57.4	20
Y + LLCon	65.6	9
Y + JR + LLCon	65.7	10
Y + MR + LLCon	67.4	10
Y + MR + JR + LLCon	67.5	11
Y + MR + LLCon + (MR × LLCon)	71.1	13
Y + JR + LLCon + (JR × LLCon)	71.2	13
Y + MR + JR + LLCon + (MR × LLCon) + (JR × LLCon)	76.6	17
Y + MR + JR + LLGCom + LLGCom^2 + (MR × LLGCom) + (JR × LLGCom)	87.6	12

Table B-1 (cont'd)

Y + JR + LLGCom + $LLGCom^2$ + (JR × LLGCom)	89.8	10
Y + JR + LLGCom + $LLGCom^2$	91.4	9
Y + LLGCom + $LLGCom^2$	91.8	8
Y + MR + LLGCom + $LLGCom^2$ + (MR × LLGCom)	92.4	10
Y + MR + JR + LLGCom + $LLGCom^2$	93.4	10
Y + MR + LLGCom + $LLGCom^2$	93.8	9
Y + MR + JR + LLGCom + (MR × LLGCom) + (JR × LLGCom)	97.2	11
Y + JR	98.2	7
Y	98.6	6
Y + JR + LLGCom + (JR × LLGCom)	99.6	9
Y + JR + LLGCom	100	8
Y + MR + JR	100.2	8
Y + MR + LLGCom + (MR × LLGCom)	100.3	9
Y + LLGCom	100.4	7
Y + MR	100.5	7
Y + MR + JR + LLGCom	102	9
Y + MR + LLGCom	102.4	8

Y [a]: Yr

JR [b]: June Rainfall

LLCom [c]: Landscape-level Composition: deciduous forest (DF)_ proportion (PLAND), evergreen forest (EF)_PLAND, mixed forest (MF)_PLAND, grassland (GL)_PLAND, pasture and hay (PH)_PLAND, and cultivated land (CL)_PLAND

Table B-1 (cont'd)

LLCom^{2} [d]: Landscape-level Composition^{2}: DF_PLAND^{2}, EF_PLAND^{2}, MF_PLAND^{2}, GL_PLAND^{2}, PH_PLAND^{2}, and CL_PLAND^{2}

LLCon [e]: Landscape-level Configuration: edge density(ED), contrast-weighted (CW)ED, and interspersion and juxtaposition (IJI)

LLCon^{2} [f]: Landscape-level Configuration^{2}: ED^{2}, CWED^{2}, and IJI^{2}

CLCon [g]: Class-level Configuration: DF_ median patch area (AREA_MD), DF_ CV of patch areas (AREA_CV), DF_ mean shape index (MSI), EF_ AREA_MD, EF_ AREA_CV, EF_ MSI, EF_ CWED, MF_ AREA_MD, MF_ AREA_CV, MF_ MSI, and MF_ CWED

MR [h]: May Rainfall

LLGCom [i]: Landscape-level Generalized Composition: forested (F)_PLAND and open (O)_PLAND

LLGCom^{2} [i]: Landscape-level Generalized Composition^{2}: F_PLAND^{2} and O_PLAND^{2}

Table B-2. Coeff. estimates for the drivers of fall harvest of wild turkeys in southwest New York during 1984-2009 from the top model, Y + JR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon.

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	−0.91296	0.09497	−9.61	<2e−16
yr	−0.01931	0.01313	−1.47	0.1414
JR	−0.07737	0.02982	−2.59	0.0095
ED	−0.01947	0.06153	−0.32	0.7516
ED^2	−0.04661	0.02186	−2.13	0.033
CWED	0.06451	0.06068	1.06	0.2877
$CWED^2$	0.00965	0.0222	0.43	0.6637
IJI	0.01183	0.08293	0.14	0.8865
IJI^2	0.00987	0.02365	0.42	0.6766
CL_PLAND	−0.10764	0.08139	−1.32	0.186
CL_PLAND^2	−0.01611	0.02415	−0.67	0.5048
PH_PLAND	−0.15504	0.1345	−1.15	0.249
PH_PLAND^2	−0.0353	0.02739	−1.29	0.1975
GL_PLAND	0.09411	0.0613	1.54	0.1248
GL_PLAND^2	−0.02011	0.02318	−0.87	0.3856
DF_PLAND	−0.11924	0.18385	−0.65	0.5166
DF_PLAND^2	−0.01773	0.04738	−0.37	0.7082
EF_PLAND	0.23542	0.07493	3.14	0.0017
EF_PLAND^2	−0.0556	0.01883	−2.95	0.0031
MF_PLAND	−0.31408	0.11847	−2.65	0.008
MF_PLAND^2	0.03589	0.03165	1.13	0.2567
DF_MSI	0.02511	0.02406	1.04	0.2966
EF_CWED	0.00509	0.04902	0.1	0.9172
EF_MSI	−0.03493	0.0361	−0.97	0.3332
MF_MSI	−0.01514	0.03868	−0.39	0.6955

Table B-2 (cont'd)

DF_AREA_MD	0.01412	0.0277	0.51	0.6103
DF_AREA_CV	−0.07763	0.03307	−2.35	0.0189
EF_AREA_MD	−0.07176	0.02551	−2.81	0.0049
EF_AREA_CV	0.05518	0.02546	2.17	0.0302
MF_AREA_MD	−0.10217	0.03137	−3.26	0.0011

Table B-3. Model set for analysis of drivers of fall harvest of wild turkeys in the Central Appalachians of New York during 1984-2009. Models below are for fixed effects only. Each of the models included all the random effects and the error structure previously chosen by AIC. K is the number of parameters.

Model name	ΔAIC	K
Y [a] + MR [b] + LLGCom [c] + $LLGCom^2$ [d] + LLCon [e] + $LLCon^2$ [f] + CLCon [g]	0	27
Y + MR + JR [h] + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon	0.4	28
Y + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	6.8	42
Y + MR + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon)	8.6	58
Y + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon	10.7	26
Y + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon	11.6	27
Y + MR + JR + LLGCom + $LLGCom^2$ + (MR × LLGCom) + (JR × LLGCom)	13.3	16
Y + MR + JR + LLGCom + $LLGCom^2$	16.9	12
Y + MR + LLGCom + $LLGCom^2$	18.9	11
Y + MR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon)	20.9	42
Y + MR + LLGCom + $LLGCom^2$ + (MR × LLGCom)	21.7	13
Y + JR + LLGCom + $LLGCom^2$ + (JR × LLGCom)	23.2	13

Table B-3 (cont'd)

Y + MR + LLCom [i] + LLCom^2 [j] + LLCon + LLCon^2 + CLCon	23.4	35
Y + MR + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	23.6	36
Y + MR + JR + LLCom	28.3	14
Y + JR + LLGCom + LLGCom^2	28.8	11
Y + MR + LLCom	29.9	13
Y + LLGCom + LLGCom^2	30.1	10
Y + MR + JR + LLCom + LLCom^2	31.9	20
Y + MR + LLCom + LLCom^2	32.4	19
Y + MR + JR + LLCom + (MR × LLCom) + (JR × LLCom)	34.1	26
Y + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	34.7	35
Y + MR + JR + LLCom + LLCom^2 + (MR × LLCom) + (JR × LLCom)	36.7	32
Y + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (JR × LLCon) + (JR × CLCon)	37.1	48
Y + JR + LLCom + (JR × LLCom)	37.3	19
Y + JR + LLCom	39.3	13
Y + MR + LLCom + (MR × LLCom)	39.5	19
Y + MR + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLCon) + (MR × CLCon) + (JR × LLCon) + (JR × CLCon)	39.8	62
Y + MR + JR + LLCon + LLCon^2	40.1	14
Y + LLCom	40.3	12
Y + JR + LLCom + LLCom^2 + (JR × LLCom)	40.9	25
Y + MR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLCon) + (MR × CLCon)	40.9	48
Y + MR + JR + LLCom + LLCon + CLCon	41	27

Table B-3 (cont’d)

Y + MR + JR + LLGCom + LLCon + CLCon	41	23
Y + MR + LLCom + $LLCom^2$ + (MR × LLCom)	41.4	25
Y + MR + LLGCom + LLCon + CLCon	41.6	2
Y + MR + LLCom + LLCon + CLCon	41.7	26
Y + LLCom + $LLCom^2$	43.3	18
Y + JR + LLCom + $LLCom^2$	43.3	19
Y + JR + LLGCom + LLCon + CLCon + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	43.6	37
Y + MR + LLCon + $LLCon^2$	43.9	13
Y + MR + JR + LLCon	46.8	11
Y + MR + JR + LLGCom + LLCon + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	47.2	53
Y + MR + JR + LLCon + $LLCon^2$ + (MR × LLCon)	48.3	20
Y + MR + LLCon + $LLCon^2$ + (MR × LLCon)	49.4	16
Y + MR + LLCon	50.3	10
Y + JR + LLCon + $LLCon^2$	50.3	13
Y + MR + JR	50.4	8
Y + JR + LLCom + LLCon + CLCon	51.2	26
Y + JR + LLGCom + LLCon + CLCon	51.3	22
Y + LLGCom + LLCon + CLCon	51.3	21
Y + LLCom + LLCon + CLCon	51.3	25
Y + MR + JR + LLGCom	52.1	10
Y + MR + JR + LLGCom + (MR × LLGCom) + (JR × LLGCom)	52.3	14

Table B-3 (cont'd)

Y + MR	53.1	7
Y + JR + LLCon + LLCon^2 + (JR × LLCon)	53.1	16
Y + LLCon + LLCon^2	53.5	12
Y + MR + LLGCom	54.8	9
Y + JR + LLCon	56.3	10
Y + JR + LLCom + LLCon + CLCon + (JR × LLCon) + (JR × CLCon)	56.9	39
Y + MR + JR + LLCon + (MR × LLCon) + (JR × LLCon)	57.4	17
Y + MR + LLGCom + (MR × LLGCom)	58.2	11
Y + MR + LLCom + LLCon + CLCon + (MR × LLCon) + (MR × CLCon)	58.8	39
Y + LLCon	59.4	9
Y + JR + LLGCom + (JR × LLGCom)	60.1	11
Y + JR + LLCon + (JR × LLCon)	61.1	13
Y + MR + JR + LLCom + LLCon + CLCon + (MR × LLCon) + (MR × CLCon) + (JR × LLCon) + (JR × CLCon)	61.1	53
Y + JR	62	7
Y + MR + LLGCom + LLCon + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon)	62.2	37
Y + JR + LLGCom	63.6	9
Y	64	6
Y + LLGCom	65.6	8

Y [a]: Yr

MR [b]: May Rainfall

LLGCom [c]: Landscape-level Generalized Composition: forested (F)_PLAND and open (O)_PLAND

Table B-3 (cont'd)

LLGCom^{2} [d]: Landscape-level Generalized Composition^{2}: F_PLAND^{2} and O_PLAND^{2}

LLCon [e]: Landscape-level Configuration: edge density(ED), contrast-weighted (CW)ED, and interspersion and juxtaposition (IJI)

LLCon^{2} [f]: Landscape-level Configuration^{2}: ED^{2}, CWED^{2}, and IJI^{2}

CLCon [g]: Class-level Configuration: DF_ median patch area (AREA_MD), DF_ CV of patch areas (AREA_CV), DF_ mean shape index (MSI), EF_ AREA_MD, EF_ AREA_CV, EF_ MSI, EF_ CWED, MF_ AREA_MD, MF_ AREA_CV, MF_ MSI, and MF_ CWED

JR [h]: June Rainfall

LLCom [i]: Landscape-level Composition: deciduous forest (DF)_ proportion (PLAND), evergreen forest (EF)_PLAND, mixed forest (MF)_PLAND, grassland (GL)_PLAND, pasture and hay (PH)_PLAND, and cultivated land (CL)_PLAND

LLCom^{2} [j]: Landscape-level Composition^{2}: DF_PLAND^{2}, EF_PLAND^{2}, MF_PLAND^{2}, GL_PLAND^{2}, PH_PLAND^{2}, and CL_PLAND^{2}

Table B-4. Coeff. estimates for the drivers of fall harvest of wild turkeys in the Central Appalachians of New York during 1984-2009 from the top model, Y + MR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon.

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	−1.38897	0.06823	−20.36	< 2e−16
yr	0.01753	0.01087	1.61	0.10667
MR	−0.14514	0.03989	−3.64	0.00027
ED	−0.12043	0.05318	−2.26	0.02354
ED^2	−0.02021	0.02004	−1.01	0.31332
CWED	−0.31473	0.06978	−4.51	6.50E−06
$CWED^2$	0.16034	0.02878	5.57	2.50E−08
IJI	0.08419	0.06729	1.25	0.2109
IJI^2	0.02945	0.0285	1.03	0.3014
O_PLAND	0.25701	0.08274	3.11	0.00189
O_PLAND^2	0.03466	0.03513	0.99	0.32378
F_PLAND	0.08931	0.0796	1.12	0.26185
F_PLAND^2	−0.19274	0.03915	−4.92	8.50E−07
DF_MSI	0.00509	0.03399	0.15	0.88102
EF_CWED	0.12599	0.04214	2.99	0.00279
EF_MSI	−0.01803	0.0396	−0.46	0.64891
MF_CWED	−0.00478	0.04599	−0.1	0.91715
MF_MSI	0.04809	0.04256	1.13	0.2585
DF_AREA_MD	0.13562	0.0357	3.8	0.00015
DF_AREA_CV	0.00523	0.03887	0.13	0.89289
EF_AREA_MD	0.01334	0.02871	0.46	0.64208
EF_AREA_CV	0.0412	0.02808	1.47	0.14232
MF_AREA_MD	0.05216	0.02928	1.78	0.07485

Table B-5. Model set for analysis of drivers of fall harvest of wild turkeys in the Eastern Appalachians and Taconic Hills of New York during 1984-2009. Models below are for fixed effects only. Each of the models included all the random effects and the error structure previously chosen by AIC. K is the number of parameters.

Model name	ΔAIC	K
Y [a] + MR [b] + JR [c] + LLGCom [d] + LLGCom^2 [e] + LLCon [f] + LLCon^2 [g] + CLCon [h] + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR ×	0	48
Y + MR + JR + LLCom [i] + LLCom^2 [j] + (MR × LLCom) + (JR × LLCom)	12	32
Y + MR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon)	12.4	35
Y + MR + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLCon) + (MR × CLCon) + (JR × LLCon) + (JR × CLCon)	13.4	54
Y + MR + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon	14.6	24
Y + MR + JR + LLCon + LLCon^2 + (MR × LLCon)	15.4	20
Y + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	16	35
Y + MR + JR + LLGCom + LLCon + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	19.4	44
Y + MR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLCon) + (MR × CLCon)	21.6	42
Y + MR + JR + LLCom + (MR × LLCom) + (JR × LLCom)	23.4	26
Y + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon	24.6	23
Y + JR + LLCom + LLCom^2 + (JR × LLCom)	24.8	25
Y + MR + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	24.8	32
Y + MR + LLCon + LLCon^2 + (MR × LLCon)	26.2	16
Y + MR + JR + LLCon + LLCon^2	26.4	14
Y + MR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon	29	23
Y + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (JR × LLCon) + (JR × CLCon)	30.2	42

Table B-5 (cont'd)

$Y + MR + LLGCom + LLCon + CLCon + (MR \times LLGCom) + (MR \times LLCon) + (MR \times CLCon)$	31.6	31
$Y + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon$	33.4	31
$Y + MR + JR + LLCom + LLCon + CLCon + (MR \times LLCon) + (MR \times CLCon) + (JR \times LLCon) + (JR \times CLCon)$	33.4	46
$Y + MR + JR + LLGCom + LLCon + CLCon$	34.8	20
$Y + JR + LLCon + LLCon^2 + (JR \times LLCon)$	35.2	16
$Y + JR + LLGCom + LLCon + CLCon + (JR \times LLGCom) + (JR \times LLCon) + (JR \times CLCon)$	36.2	31
$Y + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon$	36.4	22
$Y + MR + JR + LLCon + (MR \times LLCon) + (JR \times LLCon)$	37.2	17
$Y + MR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon$	37.4	31
$Y + JR + LLCon + LLCon^2$	37.4	13
$Y + MR + JR + LLCom + LLCom^2$	38.2	20
$Y + MR + LLCom + LLCom^2 + (MR \times LLCom)$	38.8	25
$Y + JR + LLCom + (JR \times LLCom)$	39.2	19
$Y + MR + LLCon + LLCon^2$	41.2	13
$Y + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon$	43.6	30
$Y + JR + LLGCom + LLCon + CLCon$	45	19
$Y + MR + LLCom + LLCon + CLCon + (MR \times LLCon) + (MR \times CLCon)$	46	34
$Y + MR + JR + LLCom + LLCon + CLCon$	47	24
$Y + JR + LLCom + LLCom^2$	48.2	19
$Y + MR + LLGCom + LLCon + CLCon$	48.4	19
$Y + MR + JR + LLGCom + LLGCom^2 + (MR \times LLGCom) + (JR \times LLGCom)$	48.6	12

Table B-5 (cont'd)

Y + LLCon + LLCon^2	49.2	12
Y + MR + JR + LLCom	49.4	14
Y + MR + JR + LLCon	50.2	11
Y + MR + LLCom + (MR × LLCom)	50.4	19
Y + MR + LLCon + (MR × LLCon)	51.8	13
Y + JR + LLCom + LLCon + CLCon + (JR × LLCon) + (JR × CLCon)	51.8	34
Y + MR + LLCom + LLCom^2	55	19
Y + LLGCom + LLCon + CLCon	56	18
Y + JR + LLCon + (JR × LLCon)	56.4	13
Y + MR + JR + LLGCom + (MR × LLGCom) + (JR × LLGCom)	56.4	11
Y + JR + LLCom + LLCon + CLCon	57.6	23
Y + MR + LLCom + LLCon + CLCon	60.6	23
Y + JR + LLGCom + LLGCom^2 + (JR × LLGCom)	61.4	10
Y + JR + LLCon	61.6	10
Y + JR + LLCom	62	13
Y + LLCom + LLCom^2	62.2	18
Y + MR + JR + LLGCom + LLGCom^2	62.4	10
Y + MR + LLCon	65.2	10
Y + MR + LLCom	67.4	13
Y + LLCom + LLCon + CLCon	68.4	22
Y + JR + LLGCom + (JR × LLGCom)	68.8	9

Table B-5 (cont'd)

Y + MR + JR + LLGCom	70.8	9
Y + LLCon	73.6	9
Y + LLCom	76.8	12
Y + MR + LLGCom + LLGCom^2 + (MR × LLGCom)	78.2	10
Y + JR + LLGCom + LLGCom^2	79	9
Y + MR + JR	82	8
Y + MR + LLGCom + (MR × LLGCom)	84.6	9
Y + JR + LLGCom	86.8	8
Y + MR + LLGCom + LLGCom^2	88.2	9
Y + MR + LLGCom	94.6	8
Y + JR	98.2	7
Y + LLGCom + LLGCom^2	100.8	8
Y + MR	104.2	7
Y + LLGCom	106.8	7
Y	116.6	6

Y [a]: Yr

MR [b]: May Rainfall

JR [c]: June Rainfall

LLGCom [d]: Landscape-level Generalized Composition: forested (F)_PLAND and open (O)_PLAND

LLGCom^2 [e]: Landscape-level Generalized Composition^2: F_PLAND^2 and O_PLAND^2

Table B-5 (cont'd)

LLCon [f]: Landscape-level Configuration: edge density(ED), contrast-weighted (CW)ED, and interspersion and juxtaposition (IJI)

$LLCon^2$ [g]: Landscape-level $Configuration^2$: ED^2, $CWED^2$, and IJI^2

CLCon [h]: Class-level Configuration: DF_ median patch area (AREA_MD), DF_ CV of patch areas (AREA_CV), DF_ mean shape index (MSI), EF_ AREA_MD, EF_ AREA_CV, EF_ MSI, EF_ CWED, MF_ AREA_MD, MF_ AREA_CV, MF_ MSI, and MF_ CWED

LLCom [i]: Landscape-level Composition: deciduous forest (DF)_ proportion (PLAND), evergreen forest (EF)_PLAND, mixed forest (MF)_PLAND, grassland (GL)_PLAND, pasture and hay (PH)_PLAND, and cultivated land (CL)_PLAND

$LLCom^2$ [j]: Landscape-level $Composition^2$: DF_PLAND^2, EF_PLAND^2, MF_PLAND^2, GL_PLAND^2, PH_PLAND^2, and CL_PLAND^2

Table B-6. Coeff. estimates for the drivers of fall harvest of wild turkeys in the Eastern Appalachians and Taconic Hills of New York during 1984-2009 from the top model, Y + MR + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon).

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	−1.063591	0.1008	−10.55	< 2e−16
yr	0.109246	0.013187	8.28	< 2e−16
MR	−0.094125	0.031361	−3	0.00269
JR	−0.087435	0.030859	−2.83	0.00461
ED	0.004891	0.028183	0.17	0.86222
ED^2	0.035552	0.01673	2.13	0.03358
CWED	0.225388	0.035432	6.36	2.00E−10
CWED^2	−0.077886	0.020475	−3.8	0.00014
IJI	−0.042288	0.038253	−1.11	0.26895
IJI^2	0.013092	0.018737	0.7	0.48474
O_PLAND	0.119645	0.038056	3.14	0.00167
O_PLAND^2	−0.050196	0.022241	−2.26	0.02401
DF_MSI	0.048647	0.025874	1.88	0.06009
EF_CWED	−0.050459	0.028799	−1.75	0.07975
EF_MSI	−0.080502	0.03918	−2.05	0.03991
MF_MSI	−0.032209	0.033374	−0.97	0.33451
DF_AREA_MD	−0.03224	0.025019	−1.29	0.19754
DF_AREA_CV	−0.040409	0.027629	−1.46	0.14359
EF_AREA_MD	0.082946	0.031066	2.67	0.00759
EF_AREA_CV	0.019417	0.026931	0.72	0.47091
MR × ED	0.03202	0.018689	1.71	0.08666
MR × CWED	−0.011264	0.017813	−0.63	0.52717
MR × IJI	0.074724	0.022514	3.32	0.0009
MR × O_PLAND	−0.010258	0.025159	−0.41	0.68349

Table B-6 (cont’d)

MR × DF_MSI	−0.035094	0.018448	−1.9	0.05713
MR × EF_CWED	−0.050536	0.018047	−2.8	0.00511
MR × EF_MSI	0.014828	0.026613	0.56	0.5774
MR × MF_MSI	−0.027596	0.025105	−1.1	0.27166
MR × DF_AREA_MD	0.004556	0.018559	0.25	0.8061
MR × DF_AREA_CV	0.003521	0.017009	0.21	0.836
MR × EF_AREA_MD	0.024966	0.023809	1.05	0.29436
MR × EF_AREA_CV	0.000422	0.016412	0.03	0.9795
JR × ED	0.01089	0.015949	0.68	0.49475
JR × CWED	−0.005843	0.019573	−0.3	0.7653
JR × IJI	−0.046439	0.021868	−2.12	0.0337
JR × O_PLAND	0.059434	0.022042	2.7	0.00701
JR × DF_MSI	0.017996	0.01597	1.13	0.2598
JR × EF_CWED	0.000355	0.017698	0.02	0.98399
JR × EF_MSI	−0.007887	0.023808	−0.33	0.74045
JR × MF_MSI	0.022615	0.021405	1.06	0.29073
JR × DF_AREA_MD	−0.01157	0.016053	−0.72	0.47107
JR × DF_AREA_CV	−0.029334	0.017415	−1.68	0.0921
JR × EF_AREA_MD	−0.01863	0.019981	−0.93	0.35114
JR × EF_AREA_CV	−0.020279	0.015885	−1.28	0.20173

Table B-7. Model set for analysis of drivers of fall harvest of wild turkeys in the Hudson and Mohawk River Valleys of New York during 1984-2009. Models below are for fixed effects only. Each of the models included all the random effects and the error structure previously chosen by AIC. K is the number of parameters.

Model name	ΔAIC	K
Y [a] + MR [b] + JR [c] + LLCom [d] + $LLCom^2$ [e] + LLCon [f] + $LLCon^2$ [g] + CLCon [h]	0	35
Y + MR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon	1	34
Y + JR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon + (JR × LLCon) + (JR × CLCon)	4	46
Y + MR + JR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLCon) + (MR × CLCon) + (JR × LLCon) + (JR × CLCon)	5.3	59
Y + MR + JR + LLCom + LLCon + CLCon	7.8	26
Y + MR + LLCom + LLCon + CLCon	8.8	25
Y + JR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon	9.1	34
Y + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon	9.9	33
Y + MR + JR + LLCom + $LLCom^2$	10.5	20
Y + MR + LLCom + $LLCom^2$	11.5	19
Y + JR + LLCom + LLCon + CLCon + (JR × LLCon) + (JR × CLCon)	11.6	37
Y + MR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLCon) + (MR × CLCon)	12.3	46
Y + MR + JR + LLCom + LLCon + CLCon + (MR × LLCon) + (MR × CLCon) + (JR × LLCon) + (JR × CLCon)	12.4	50
Y + MR + JR + LLCom	12.4	14
Y + MR + LLCom	13.3	13
Y + MR + JR + LLGCom [i] + LLCon + CLCon	15.6	22
Y + MR + LLGCom + LLCon + CLCon	16.3	21

Table B-7 (cont'd)

Y + JR + LLCom + LLCom^2 + (JR × LLCom)	16.4	25
Y + MR + JR + LLGCom + LLCon + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	16.7	50
Y + MR + JR + LLCom + LLCom^2 + (MR × LLCom) + (JR × LLCom)	17.5	32
Y + JR + LLCom + LLCon + CLCon	17.9	25
Y + JR + LLCom + (JR × LLCom)	18.7	19
Y + MR + JR + LLCom + (MR × LLCom) + (JR × LLCom)	18.8	26
Y + LLCom + LLCon + CLCon	18.9	24
Y + MR + LLCom + LLCom^2 + (MR × LLCom)	18.9	25
Y + JR + LLCom + LLCom^2	19.9	19
Y + LLCom + LLCom^2	20.9	18
Y + MR + LLCom + LLCon + CLCon + (MR × LLCon) + (MR × CLCon)	20.9	37
Y + MR + LLCom + (MR × LLCom)	21.1	19
Y + MR + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon)	21.1	55
Y + MR + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon	21.2	27
Y + JR + LLGCom + LLCon + CLCon + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	21.3	35
Y + MR + LLGCom + LLCon + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon)	21.5	35
Y + MR + LLGCom + LLGCom$^{2\ j}$ + LLCon + LLCon^2 + CLCon	21.8	26
Y + JR + LLCom	22.7	13
Y + LLCom	23.6	12
Y + MR + JR + LLCon + (MR × LLCon) + (JR × LLCon)	24.6	17
Y + JR + LLGCom + LLCon + CLCon	25.3	21

Table B-7 (cont'd)

Y + MR + LLGCom + LLGCom^2 + (MR × LLGCom)	25.9	13
Y + LLGCom + LLCon + CLCon	25.9	20
Y + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	26	40
Y + MR + LLGCom + (MR × LLGCom)	26.1	11
Y + MR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon)	26.7	40
Y + MR + JR + LLCon	26.8	11
Y + MR + JR + LLCon + LLCon^2 + (MR × LLCon)	28.3	20
Y + MR + JR + LLGCom + LLGCom^2	28.7	12
Y + MR + LLCon	28.9	10
Y + MR + LLGCom + LLGCom^2	29.3	11
Y + MR + LLCon + (MR × LLCon)	29.4	13
Y + MR + JR + LLGCom + LLGCom^2 + (MR × LLGCom) + (JR × LLGCom)	29.6	16
Y + MR + JR + LLGCom + (MR × LLGCom) + (JR × LLGCom)	29.6	14
Y + MR + JR + LLGCom	30.2	10
Y + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon	30.7	26
Y + MR + JR + LLCon + LLCon^2	30.7	14
Y + MR + LLGCom	31.1	9
Y + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon	31.2	25
Y + MR + LLCon + LLCon^2	32.7	13
Y + MR + LLCon + LLCon^2 + (MR × LLCon)	33.4	16
Y + MR + JR	34.7	8

Table B-7 (cont'd)

Y + JR + LLCon + (JR × LLCon)	35.9	13
Y + MR	36	7
Y + JR + LLCon	36.1	10
Y + JR + LLGCom + LLGCom^2	38	11
Y + LLCon	38.1	9
Y + LLGCom + LLGCom^2	38.4	10
Y + JR + LLCon + LLCon^2 + (JR × LLCon)	39.4	16
Y + JR + LLGCom	39.5	9
Y + JR + LLCon + LLCon^2	39.9	13
Y + LLGCom	40.2	8
Y + JR + LLGCom + LLGCom^2 + (JR × LLGCom)	40.3	13
Y + LLCon + LLCon^2	41.7	12
Y + JR + LLGCom + (JR × LLGCom)	42	11
Y + JR	43.3	7
Y	44.6	6

Y [a]: Yr

MR [b]: May Rainfall

JR [c]: June Rainfall

LLCom [d]: Landscape-level Composition: deciduous forest (DF)_ proportion (PLAND), evergreen forest (EF)_PLAND, mixed forest (MF)_PLAND, grassland (GL)_PLAND, pasture and hay (PH)_PLAND, and cultivated land (CL)_PLAND

Table B-7 (cont'd)

LLCom^2 [e]: Landscape-level Composition^2: DF_PLAND^2, EF_PLAND^2, MF_PLAND^2, GL_PLAND^2, PH_PLAND^2, and CL_PLAND^2

LLCon [f]: Landscape-level Configuration: edge density(ED), contrast-weighted (CW)ED, and interspersion and juxtaposition (IJI)

LLCon^2 [g]: Landscape-level Configuration^2: ED^2, CWED^2, and IJI^2

CLCon [h]: Class-level Configuration: DF_ median patch area (AREA_MD), DF_ CV of patch areas (AREA_CV), DF_ mean shape index (MSI), EF_ AREA_MD, EF_ AREA_CV, EF_ MSI, EF_ CWED, MF_ AREA_MD, MF_ AREA_CV, MF_ MSI, and MF_ CWED

LLGCom [i]: Landscape-level Generalized Composition: forested (F)_PLAND and open (O)_PLAND

LLGCom^2 [j]: Landscape-level Generalized Composition^2: F_PLAND^2 and O_PLAND^2

Table B-8. Coeff. estimates for the drivers of fall harvest of wild turkeys in the Hudson and Mohawk River Valleys of New York during 1984-2009 from the top model, Y + MR + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon.

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	−1.3313	0.13278	−10.03	< 2e−16
yr	0.08276	0.01641	5.04	4.60E−07
MR	−0.16151	0.04828	−3.34	0.00082
JR	0.08379	0.04878	1.72	0.08588
ED	0.012	0.0795	0.15	0.87997
ED^2	−0.00598	0.03066	−0.19	0.84548
CWED	−0.16097	0.10482	−1.54	0.12461

Table B-8 (cont'd)

$CWED^2$	0.04632	0.02773	1.67	0.09483
IJI	0.14193	0.07501	1.89	0.05849
IJI^2	−0.02828	0.02716	−1.04	0.29776
CL_PLAND	0.05552	0.08598	0.65	0.51847
CL_PLAND^2	0.04531	0.03132	1.45	0.14799
PH_PLAND	0.46944	0.10817	4.34	1.40E−05
PH_PLAND^2	−0.02327	0.03716	−0.63	0.53123
GL_PLAND	−0.22826	0.109	−2.09	0.03625
GL_PLAND^2	0.0387	0.0351	1.1	0.27012
DF_PLAND	0.18026	0.08691	2.07	3.81E−02
DF_PLAND^2	0.02903	0.03494	0.83	0.40612
EF_PLAND	−0.26468	0.11824	−2.24	2.52E−02
EF_PLAND^2	0.135	0.0333	4.05	5.00E−05
MF_PLAND	0.42963	0.10781	3.99	6.70E−05
MF_PLAND^2	−0.05294	0.03692	−1.43	0.15155
DF_MSI	−0.04919	0.04321	−1.14	0.25495
EF_CWED	0.06995	0.05435	1.29	0.19805
EF_MSI	0.02307	0.07449	0.31	0.75681
MF_CWED	−0.21441	0.094	−2.28	0.02255
MF_MSI	−0.14586	0.05526	−2.64	0.00831
DF_AREA_MD	−0.1366	0.04597	−2.97	0.00296
DF_AREA_CV	−0.0552	0.05437	−1.02	0.31001
EF_AREA_MD	0.05089	0.08888	0.57	0.56695
EF_AREA_CV	−0.00505	0.04824	−0.1	0.91655

Table B-9. Model set for analysis of drivers of fall harvest of wild turkeys the Great Lakes Plain of New York during 1984-2009. Models below are for fixed effects only. Each of the models included all the random effects and the error structure previously chosen by AIC. K is the number of parameters.

Model name	ΔAIC	K
Y [a] + MR [b] + LLGCom [c] + $LLGCom^2$ [d] + LLCon [e] + $LLCon^2$ [f] + CLCon [g]	0	25
Y + MR + LLGCom + LLCon + CLCon	0.2	20
Y + MR + JR [h] + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon	1.9	26
Y + MR + JR + LLGCom + LLCon + CLCon	2.2	21
Y + LLGCom + LLCon + CLCon	2.9	19
Y + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon	2.9	24
Y + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon	4.6	25
Y + JR + LLGCom + LLCon + CLCon	4.6	20
Y + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	6.5	38
Y + MR + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon)	7	52
Y + JR + LLGCom + LLCon + CLCon + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	7.3	33
Y + MR + LLCom [i] + LLCon + CLCon	7.4	24
Y + MR + JR + LLGCom + LLCon + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	8.4	47
Y + MR + JR + LLCom + LLCon + CLCon	9.3	25
Y + LLCom + LLCon + CLCon	9.9	23
Y + MR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon)	10.7	38
Y + MR + LLGCom + LLCon + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon)	11	33

Table B-9 (cont'd)

Y + JR + LLCom + LLCon + CLCon	11.6	24
Y + MR + LLCom + LLCom^2 [j] + LLCon + LLCon^2 + CLCon	12.2	33
Y + MR + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	14	34
Y + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	14.9	32
Y + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	16.3	33
Y + MR + JR + LLCom + LLCom^2 + (MR × LLCom) + (JR × LLCom)	16.4	32
Y + MR + LLCom + LLCon + CLCon + (MR × LLCon) + (MR × CLCon)	16.5	35
Y + MR + JR + LLCom + LLCon + CLCon + (MR × LLCon) + (MR × CLCon) + (JR × LLCon) + (JR × CLCon)	18.8	47
Y + JR + LLCom + LLCon + CLCon + (JR × LLCon) + (JR × CLCon)	19	35
Y + MR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLCon) + (MR × CLCon)	21.2	44
Y + MR + JR + LLCom + (MR × LLCom) + (JR × LLCom)	21.9	26
Y + JR + LLCom + LLCom^2 + (JR × LLCom)	22	25
Y + MR + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLCon) + (MR × CLCon) + (JR × LLCon) + (JR × CLCon)	22.3	56
Y + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (JR × LLCon) + (JR × CLCon)	23.1	44
Y + MR + LLCom + LLCom^2 + (MR × LLCom)	23.9	25
Y + MR + LLCom + LLCom^2	24	19
Y + MR + JR + LLCom + LLCom^2	26	20
Y + JR + LLCom + (JR × LLCom)	26.9	19
Y + LLCom + LLCom^2	27.2	18
Y + MR + LLCom + (MR × LLCom)	28.4	19
Y + MR + LLCom	28.5	13

Table B-9 (cont'd)

Y + JR + LLCom + LLCom^2	28.9	19
Y + MR + JR + LLCom	30.5	14
Y + LLCom	31.5	12
Y + JR + LLCom	33.5	13
Y + MR + JR + LLGCom + LLGCom^2 + (MR × LLGCom) + (JR × LLGCom)	34.9	16
Y + MR + JR + LLGCom + (MR × LLGCom) + (JR × LLGCom)	35.4	14
Y + MR + LLGCom + (MR × LLGCom)	38.5	11
Y + MR + LLGCom + LLGCom^2 + (MR × LLGCom)	38.6	13
Y + MR + LLGCom	38.7	9
Y + MR + LLGCom + LLGCom^2	39.2	11
Y + MR + JR + LLGCom	40.1	10
Y + JR + LLGCom + (JR × LLGCom)	40.2	11
Y + JR + LLGCom + LLGCom^2 + (JR × LLGCom)	40.3	13
Y + LLGCom	40.4	8
Y + MR + JR + LLGCom + LLGCom^2	40.5	12
Y + LLGCom + LLGCom^2	40.9	10
Y + JR + LLGCom	42.1	9
Y + MR + LLCon	42.2	10
Y + JR + LLGCom + LLGCom^2	42.5	11
Y + LLCon	43.1	9
Y + MR + JR + LLCon	44.1	11

Table B-9 (cont'd)

Y + JR + LLCon	45.1	10
Y + MR + LLCon + $LLCon^2$	45.9	13
Y + LLCon + $LLCon^2$	47	12
Y + MR + LLCon + (MR × LLCon)	47.7	13
Y + MR + JR + LLCon + $LLCon^2$	47.8	14
Y + JR + LLCon + (JR × LLCon)	48	13
Y + JR + LLCon + $LLCon^2$	49	13
Y + MR + LLCon + $LLCon^2$ + (MR × LLCon)	51.4	16
Y + JR + LLCon + $LLCon^2$ + (JR × LLCon)	51.7	16
Y + MR + JR + LLCon + (MR × LLCon) + (JR × LLCon)	51.9	17
Y + MR + JR + LLCon + $LLCon^2$ + (MR × LLCon)	55.5	20
Y + MR	73.8	7
Y	74.2	6
Y + MR + JR	75.5	8
Y + JR	76.1	7

Y [a]: Yr

MR [b]: May Rainfall

LLGCom [c]: Landscape-level Generalized Composition: forested (F)_PLAND and open (O)_PLAND

$LLGCom^2$ [d]: Landscape-level Generalized $Composition^2$: F_PLAND^2 and O_PLAND^2

LLCon [e]: Landscape-level Configuration: edge density(ED), contrast-weighted (CW)ED, and interspersion and juxtaposition (IJI)

Table B-9 (cont'd)

LLCon^{2} [f]: Landscape-level Configuration^{2}: ED^{2}, CWED^{2}, and IJI^{2}

CLCon [g]: Class-level Configuration: DF_ median patch area (AREA_MD), DF_ CV of patch areas (AREA_CV), DF_ mean shape index (MSI), EF_ AREA_MD, EF_ AREA_CV, EF_ MSI, EF_ CWED, MF_ AREA_MD, MF_ AREA_CV, MF_ MSI, and MF_ CWED

JR [h]: June Rainfall

LLCom [i]: Landscape-level Composition: deciduous forest (DF)_ proportion (PLAND), evergreen forest (EF)_PLAND, mixed forest (MF)_PLAND, grassland (GL)_PLAND, pasture and hay (PH)_PLAND, and cultivated land (CL)_PLAND

LLCom^{2} [j]: Landscape-level Composition^{2}: DF_PLAND^{2}, EF_PLAND^{2}, MF_PLAND^{2}, GL_PLAND^{2}, PH_PLAND^{2}, and CL_PLAND^{2}

Table B-10. Coeff. estimates for the drivers of fall harvest of wild turkeys in the Great Lakes Plain of New York during 1984-2009 from the top model, Y + MR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon.

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	−1.19317	0.11971	−9.97	<2e−16
yr	−0.00267	0.01544	−0.17	0.8629
MR	−0.11681	0.05262	−2.22	0.0264
ED	−0.02565	0.08815	−0.29	0.7711
ED^2	−0.01769	0.03808	−0.46	0.6422
CWED	−0.14554	0.11243	−1.29	0.1955
CWED^2	0.08463	0.03821	2.21	0.0268
IJI	0.19324	0.09291	2.08	0.0375
IJI^2	−0.00647	0.03236	−0.2	0.8415
O_PLAND	−0.10993	0.10287	−1.07	0.2852
O_PLAND^2	−0.06121	0.05656	−1.08	0.2791
F_PLAND	0.17363	0.10298	1.69	0.0918
F_PLAND^2	0.10221	0.05279	1.94	0.0528
DF_MSI	0.07744	0.05047	1.53	0.1249
EF_CWED	0.31433	0.06297	4.99	6.00E−07
EF_MSI	0.02725	0.05693	0.48	0.6321
MF_MSI	−0.17447	0.06031	−2.89	0.0038
DF_AREA_MD	0.17943	0.05992	2.99	0.0027
DF_AREA_CV	−0.00733	0.06555	−0.11	0.911
EF_AREA_MD	0.00314	0.04762	0.07	0.9475
MF_AREA_MD	0.03166	0.05208	0.61	0.5432

Table B-11. Model set for analysis of drivers of fall harvest of wild turkeys the Adirondacks and Tug Hill of New York during 1984-2009. Models below are for fixed effects only. Each of the models included all the random effects and the error structure previously chosen by AIC. K is the number of parameters.

Model name	ΔAIC	K
Y [a] + JR [b] + LLCon [c] + $LLCon^2$ [d] + (JR × LLCon)	0	13
Y + JR + LLCon + (JR × LLCon)	0	16
Y + MR [e] + JR + LLCon + (MR × LLCon) + (JR × LLCon)	3.4	17
Y + MR + JR + LLCon + $LLCon^2$ + (MR × LLCon)	3.8	20
Y + JR + LLGCom [f] + $LLGCom^2$ [g] + (JR × LLGCom)	5.2	10
Y + MR + JR + LLGCom + $LLGCom^2$ + (MR × LLGCom) + (JR × LLGCom)	6.6	12
Y + MR + LLCon + $LLCon^2$	7.5	13
Y + MR + JR + LLCon + $LLCon^2$	8.2	14
Y + LLCon + $LLCon^2$	8.8	12
Y + JR + LLCon + $LLCon^2$	9.2	13
Y + JR + LLGCom + LLCon + CLCon [h] + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	10.1	31
Y + MR + LLCon	10.3	10
Y + JR + LLCom [i] + (JR × LLCom)	10.6	19
Y + MR + JR + LLCon	11.1	11
Y + MR + LLCon + $LLCon^2$ + (MR × LLCon)	12.1	16
Y + LLCon	12.5	9
Y + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	12.8	35

Table B-11 (cont'd)

Y + JR + LLCon	13	10
Y + MR + JR + LLCom + (MR × LLCom) + (JR × LLCom)	13	26
Y + MR + LLGCom + LLCon + CLCon	14	19
Y + MR + JR + LLGCom + LLCon + CLCon	14.4	20
Y + MR + LLCon + (MR × LLCon)	15.6	13
Y + MR + LLCom	16.2	13
Y + MR + JR + LLCom	16.4	14
Y + JR + LLGCom + LLCon + CLCon	16.6	19
Y + LLGCom + LLCon + CLCon	16.7	18
Y + JR + LLGCom + (JR × LLGCom)	16.9	9
Y + MR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon	17.5	23
Y + JR + LLCom + LLCom^2 [j] + (JR × LLCom)	18	25
Y + MR + JR + LLGCom + (MR × LLGCom) + (JR × LLGCom)	18.2	11
Y + MR + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon	18.2	24
Y + JR + LLCom	18.5	13
Y + LLCom	18.7	12
Y + MR + LLGCom + LLGCom^2	19.6	9
Y + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon	19.8	22
Y + MR + JR + LLGCom + LLGCom^2	19.8	10
Y + JR + LLGCom + LLGCom^2	20.1	9
Y + MR + LLGCom + LLGCom^2 + (MR × LLGCom)	20.1	10

Table B-11 (cont'd)

Y + LLGCom + LLGCom^2	20.1	8
Y + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon	20.2	23
Y + MR + JR + LLCom + LLCom^2 + (MR × LLCom) + (JR × LLCom)	20.3	32
Y + MR + LLCom + (MR × LLCom)	21.1	19
Y + JR + LLCom + LLCon + CLCon + (JR × LLCon) + (JR × CLCon)	22	34
Y + MR + LLCom + LLCon + CLCon	22.3	23
Y + MR + JR + LLCom + LLCon + CLCon	22.7	24
Y + MR + LLCom + LLCom^2	23.2	19
Y + MR + JR + LLCom + LLCom^2	23.6	20
Y + JR + LLCom + LLCon + CLCon	25.1	23
Y + LLCom + LLCon + CLCon	25.1	22
Y + LLCom + LLCom^2	25.5	18
Y + JR + LLCom + LLCom^2	25.6	19
Y + MR + JR + LLGCom + LLCon + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	26.8	44
Y + MR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	27.8	31
Y + MR + LLCom + LLCom^2 + (MR × LLCom)	28.2	25
Y + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (JR × LLCon) + (JR × CLCon)	28.3	42
Y + MR + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	28.5	32
Y + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	29.2	30
Y + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	29.6	31
Y + MR + LLGCom + LLCon + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon)	29.7	31

Table B-11 (cont'd)

Y + JR + LLGCom	29.8	8
Y + MR + JR + LLGCom	29.9	9
Y + MR + LLGCom + (MR × LLGCom)	30.2	9
Y + MR + LLGCom	30.3	8
Y + MR + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon)	30.3	48
Y + LLGCom	30.4	7
Y + MR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon)	33.6	35
Y + MR + JR + LLCom + LLCon + CLCon + (MR × LLCon) + (MR × CLCon) + (JR × LLCon) + (JR × CLCon)	37.3	46
Y + MR + LLCom + LLCon + CLCon + (MR × LLCon) + (MR × CLCon)	37.5	34
Y + MR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLCon) + (MR × CLCon)	42.4	42
Y + MR + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLCon) + (MR × CLCon) + (JR × LLCon) + (JR × CLCon)	44.3	54
Y + MR	58.2	7
Y	58.5	6
Y + MR + JR	59.1	8
Y + JR	59.2	7

Y [a]: Yr

JR [b]: June Rainfall

LLCon [c]: Landscape-level Configuration: edge density(ED), contrast-weighted (CW)ED, and interspersion and juxtaposition (IJI)

LLCon^2 [d]: Landscape-level Configuration^2: ED^2, CWED^2, and IJI^2

MR [e]: May Rainfall

Table B-11 (cont'd)

LLGCom [f]: Landscape-level Generalized Composition: forested (F)_PLAND and open (O)_PLAND

LLGCom^2 [g]: Landscape-level Generalized Composition^2: F_PLAND^2 and O_PLAND^2

CLCon [h]: Class-level Configuration: DF_ median patch area (AREA_MD), DF_ CV of patch areas (AREA_CV), DF_ mean shape index (MSI), EF_ AREA_MD, EF_ AREA_CV, EF_ MSI, EF_ CWED, MF_ AREA_MD, MF_ AREA_CV, MF_ MSI, and MF_ CWED

LLCom [i]: Landscape-level Composition: deciduous forest (DF)_ proportion (PLAND), evergreen forest (EF)_PLAND, mixed forest (MF)_PLAND, grassland (GL)_PLAND, pasture and hay (PH)_PLAND, and cultivated land (CL)_PLAND

LLCom^2 [j]: Landscape-level Composition^2: DF_PLAND^2, EF_PLAND^2, MF_PLAND^2, GL_PLAND^2, PH_PLAND^2, and CL_PLAND^2

Table B-12. Coeff. estimates for the drivers of fall harvest of wild turkeys in the Adirondacks and Tug Hill of New York during 1984-2009 from the top model, Y + JR + LLCon + (JR × LLCon).

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	−1.7966	0.1706	−10.53	< 2e−16
yr	0.0534	0.026	2.05	0.0399
JR	−0.1358	0.0964	−1.41	0.15866
ED	−0.0771	0.0732	−1.05	0.29209
CWED	0.3221	0.0903	3.57	0.00036
IJI	0.4899	0.0833	5.88	4.10E−09
JR × ED	0.0218	0.0528	0.41	0.67977
JR × CWED	0.11	0.0588	1.87	0.06147
JR × IJI	0.1563	0.0619	2.53	0.01151

Table B-13. Model set for analysis of drivers of fall harvest of wild turkeys the St. Lawrence Plain and Champlain Valley of New York during 1989-2009. Models below are for fixed effects only. Each of the models included all the random effects and the error structure previously chosen by AIC. K is the number of parameters.

Model name	ΔAIC	K
Y [a] + LLCom [b] + LLCom^2 [c]	0	18
Y + MR [d] + LLCom + LLCom^2	1.9	19
Y + JR [e] + LLCom + LLCom^2	2	19
Y + MR + JR + LLCom + LLCom^2	3.9	20
Y + LLCom	4.3	12
Y + MR + LLCom	6.2	13

Table B-13 (cont'd)

Y + JR + LLCom	6.3	13
Y + MR + LLCom + LLCom^2 + (MR × LLCom)	6.8	25
Y + MR + JR + LLCom	8.2	14
Y + JR + LLCom + LLCom^2 + (JR × LLCom)	10.1	25
Y + MR + LLCom + (MR × LLCom)	11.8	19
Y + LLGCom [f] + LLCon [g] + CLCon [h]	12.2	18
Y + LLCom + LLCom^2 + LLCon + LLCon^2 [i] + CLCon	12.5	30
Y + LLCom + LLCon + CLCon	12.9	22
Y + LLGCom	13.2	7
Y + MR + LLGCom + LLCon + CLCon	13.9	19
Y + JR + LLGCom + LLCon + CLCon	14.2	19
Y + MR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	14.2	31
Y + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	14.5	31
Y + MR + LLCom + LLCon + CLCon	14.5	23
Y + JR + LLGCom + (JR × LLGCom)	14.6	9
Y + JR + LLCom + (JR × LLCom)	14.6	19
Y + JR + LLCom + LLCon + CLCon	14.9	23
Y + JR + LLGCom	15	8
Y + MR + LLGCom	15.1	8
Y + LLGCom + LLGCom^2 [j]	15.2	8
Y + MR + JR + LLGCom + LLCon + CLCon	15.9	20

Table B-13 (cont'd)

Y + MR + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon	16.2	32
Y + MR + JR + LLCom + LLCom^2 + (MR × LLCom) + (JR × LLCom)	16.5	32
Y + MR + JR + LLCom + LLCon + CLCon	16.5	24
Y + JR + LLGCom + LLGCom^2 + (JR × LLGCom)	16.6	10
Y + MR + LLGCom + (MR × LLGCom)	16.9	9
Y + MR + JR + LLGCom	17	9
Y + JR + LLGCom + LLGCom^2	17	9
Y + MR + LLGCom + LLGCom^2	17.1	9
Y + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon	18.1	22
Y + MR + JR + LLGCom + (MR × LLGCom) + (JR × LLGCom)	18.2	11
Y + MR + LLGCom + LLCon + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon)	18.4	31
Y + MR + LLGCom + LLGCom^2 + (MR × LLGCom)	18.9	10
Y + MR + JR + LLGCom + LLGCom^2	18.9	10
Y + MR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon	19.8	23
Y + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon	20	23
Y + MR + JR + LLGCom + LLGCom^2 + (MR × LLGCom) + (JR × LLGCom)	20.2	12
Y + MR + LLCom + LLCon + CLCon + (MR × LLCon) + (MR × CLCon)	20.5	34
Y + MR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLCon) + (MR × CLCon)	20.8	42
Y + LLCon	21.3	9
Y + MR + JR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon	21.7	24

Table B-13 (cont'd)

Y + MR + JR + LLCom + (MR × LLCom) + (JR × LLCom)	21.9	26
Y + MR + LLCon + (MR × LLCon)	22.7	13
Y + JR + LLCon	22.9	10
Y + MR + LLCon	23.3	10
Y + MR + LLGCom + LLGCom^2 + LLCon + LLCon^2 + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon)	24.7	35
Y + MR + JR + LLCon	24.9	11
Y + LLCon + LLCon^2	26	12
Y + JR + LLCon + (JR × LLCon)	26.6	13
Y + MR + JR + LLCon + (MR × LLCon) + (JR × LLCon)	27.6	17
Y + MR + LLCon + LLCon^2 + (MR × LLCon)	27.6	16
Y + JR + LLCon + LLCon^2	27.7	13
Y + MR + LLCon + LLCon^2	28	13
Y	28.7	6
Y + MR + JR + LLCon + LLCon^2	29.6	14
Y + JR	30.1	7
Y + MR	30.7	7
Y + JR + LLCon + LLCon^2 + (JR × LLCon)	31.5	16
Y + JR + LLCom + LLCom^2 + LLCon + LLCon^2 + CLCon + (JR × LLCon) + (JR × CLCon)	32.1	42
Y + MR + JR	32.1	8
Y + JR + LLCom + LLCon + CLCon + (JR × LLCon) + (JR × CLCon)	32.4	34

Table B-13 (cont'd)

Y + MR + JR + LLCon + $LLCon^2$ + (MR × LLCon)	32.7	20
Y + JR + LLGCom + LLCon + CLCon + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	33.1	31
Y + MR + JR + LLGCom + LLCon + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	38.5	44
Y + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	39.4	35
Y + MR + JR + LLCom + LLCon + CLCon + (MR × LLCon) + (MR × CLCon) + (JR × LLCon) + (JR × CLCon)	40.1	46
Y + MR + JR + LLCom + $LLCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLCon) + (MR × CLCon) + (JR × LLCon) + (JR × CLCon)	40.6	54
Y + MR + JR + LLGCom + $LLGCom^2$ + LLCon + $LLCon^2$ + CLCon + (MR × LLGCom) + (MR × LLCon) + (MR × CLCon) + (JR × LLGCom) + (JR × LLCon) + (JR × CLCon)	45.1	48

Y [a]: Yr

LLCom [b]: Landscape-level Composition: deciduous forest (DF)_ proportion (PLAND), evergreen forest (EF)_PLAND, mixed forest (MF)_PLAND, grassland (GL)_PLAND, pasture and hay (PH)_PLAND, and cultivated land (CL)_PLAND

$LLCom^2$ [c]: Landscape-level $Composition^2$: DF_PLAND^2, EF_PLAND^2, MF_PLAND^2, GL_PLAND^2, PH_PLAND^2, and CL_PLAND^2

MR [d]: May Rainfall

JR [e]: June Rainfall

LLGCom [f]: Landscape-level Generalized Composition: forested (F)_PLAND and open (O)_PLAND

LLCon [g]: Landscape-level Configuration: edge density(ED), contrast-weighted (CW)ED, and interspersion and juxtaposition (IJI)

Table B-13 (cont'd)

CLCon[h]: Class-level Configuration: DF_ median patch area (AREA_MD), DF_ CV of patch areas (AREA_CV), DF_ mean shape index (MSI), EF_ AREA_MD, EF_ AREA_CV, EF_ MSI, EF_ CWED, MF_ AREA_MD, MF_ AREA_CV, MF_ MSI, and MF_ CWED

LLCon^2[i]: Landscape-level Configuration^2: ED^2, CWED^2, and IJI^2

LLGCom^2[j]: Landscape-level Generalized Composition^2: F_PLAND^2 and O_PLAND^2

Table B-14. Coeff. estimates for the drivers of fall harvest of wild turkeys in the St. Lawrence Plain and Champlain Valley of New York during 1989-2009 from the top model, Y + LLCom + $LLCom^2$.

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	−1.5513	0.197	−7.87	3.50E−15
yr	0.0302	0.0207	1.45	0.146
CL_PLAND	−0.0687	0.1524	−0.45	0.6522
CL_PLAND^2	0.1113	0.0769	1.45	0.1478
PH_PLAND	0.1419	0.1408	1.01	0.3136
PH_PLAND^2	−0.1199	0.0814	−1.47	0.141
GL_PLAND	−0.1554	0.1228	−1.27	0.2057
GL_PLAND^2	0.0851	0.0393	2.17	0.0302
DF_PLAND	0.0854	0.1383	0.62	0.537
DF_PLAND^2	−0.0756	0.0747	−1.01	0.3115
EF_PLAND	−0.3119	0.167	−1.87	0.0619
EF_PLAND^2	0.1524	0.0829	1.84	0.0659
MF_PLAND	−0.8339	0.2146	−3.89	0.0001
MF_PLAND^2	0.1802	0.0848	2.13	0.0335

APPENDIX C. EFFECTS PLOTS FOR COVARIATE EFFECTS ON FALL WILD TURKEY HARVEST IN NEW YORK STATE.

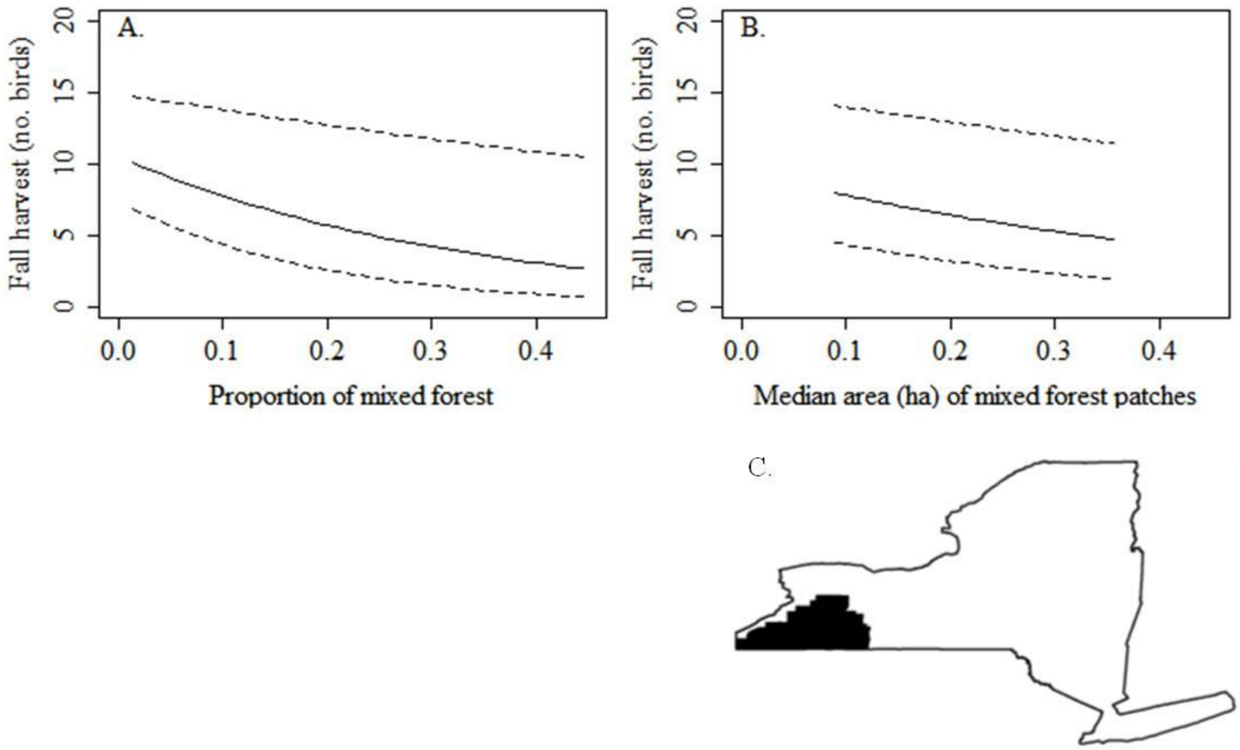

Figure C-1. Proportion of mixed forest (A) and median area of mixed forest patches (B) effects on township-level fall wild turkey harvest (adjusted by effort) in southwest New York State (C) from 1984−2009 (95% confidence intervals indicated by dashed lines).

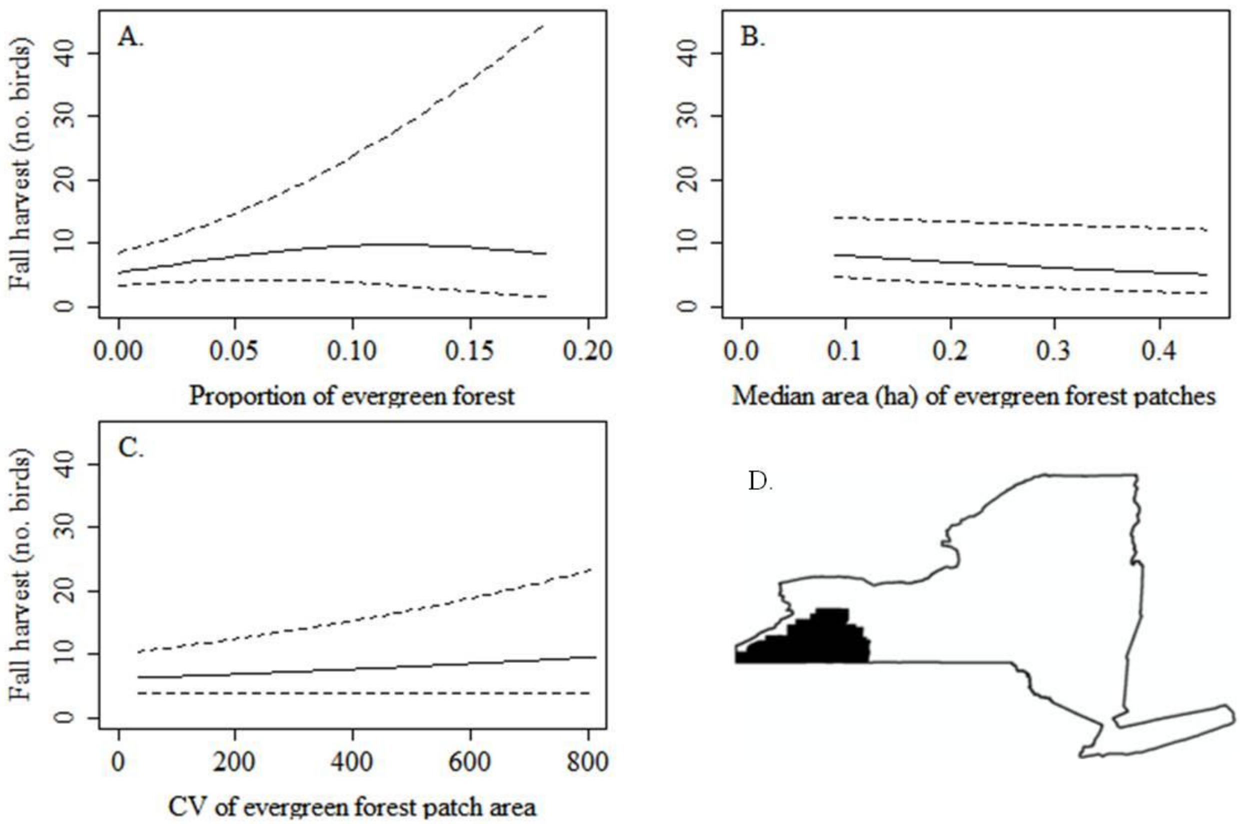

Figure C-2. Proportion of evergreen forest (A), median area of evergreen forest patches (B), and the CV of evergreen forest patch area (C) effects on township-level fall wild turkey harvest (adjusted by effort) in southwest New York State (D) from 1984−2009 (95% confidence intervals indicated by dashed lines).

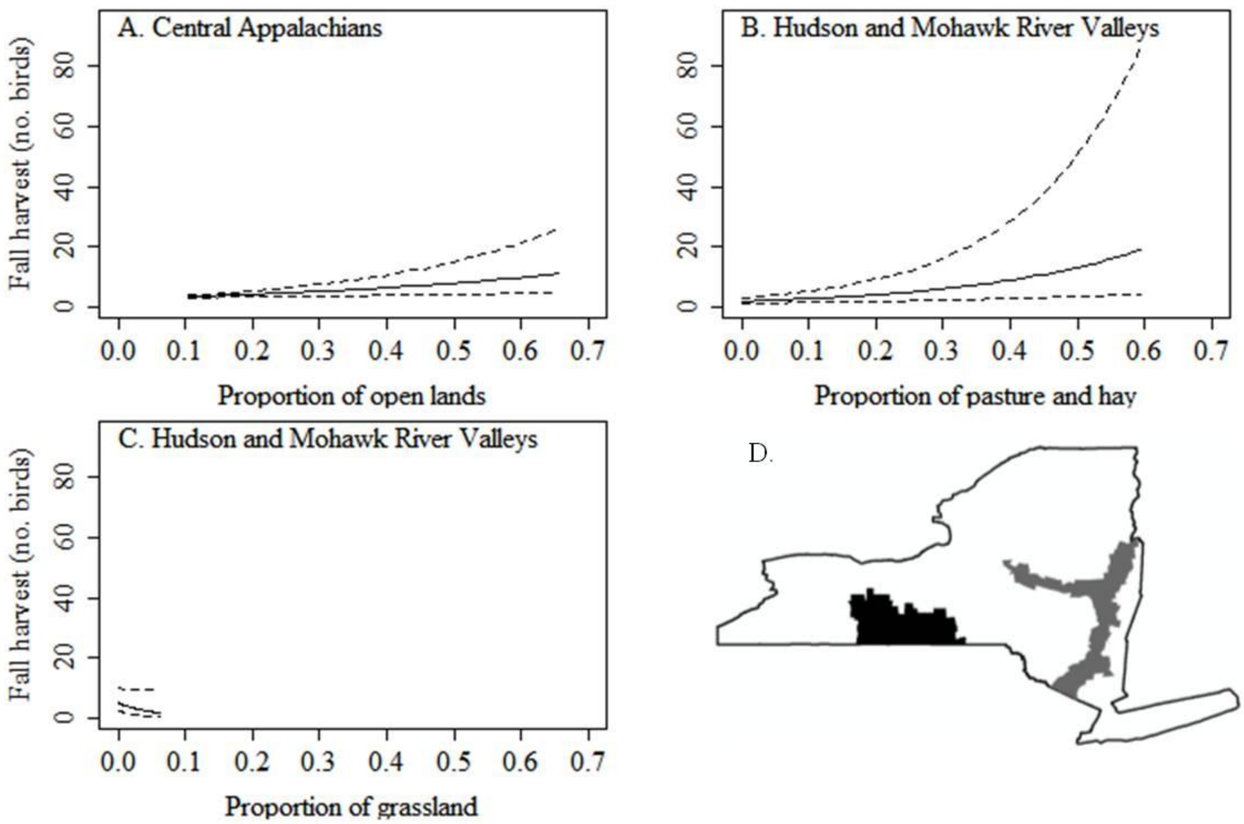

Figure C-3. Proportion of different open cover types effects on township-level fall wild turkey harvest (adjusted by effort) in across several climate-ecozones in New York State (D) from 1984−2009 (95% confidence intervals indicated by dashed lines). The proportion of all 3 open cover types together affected fall harvest in the Central Appalachians (A), and the proportions of pasture and hay (B) and grassland (C) affected fall harvest in the Hudson and Mohawk River Valleys.

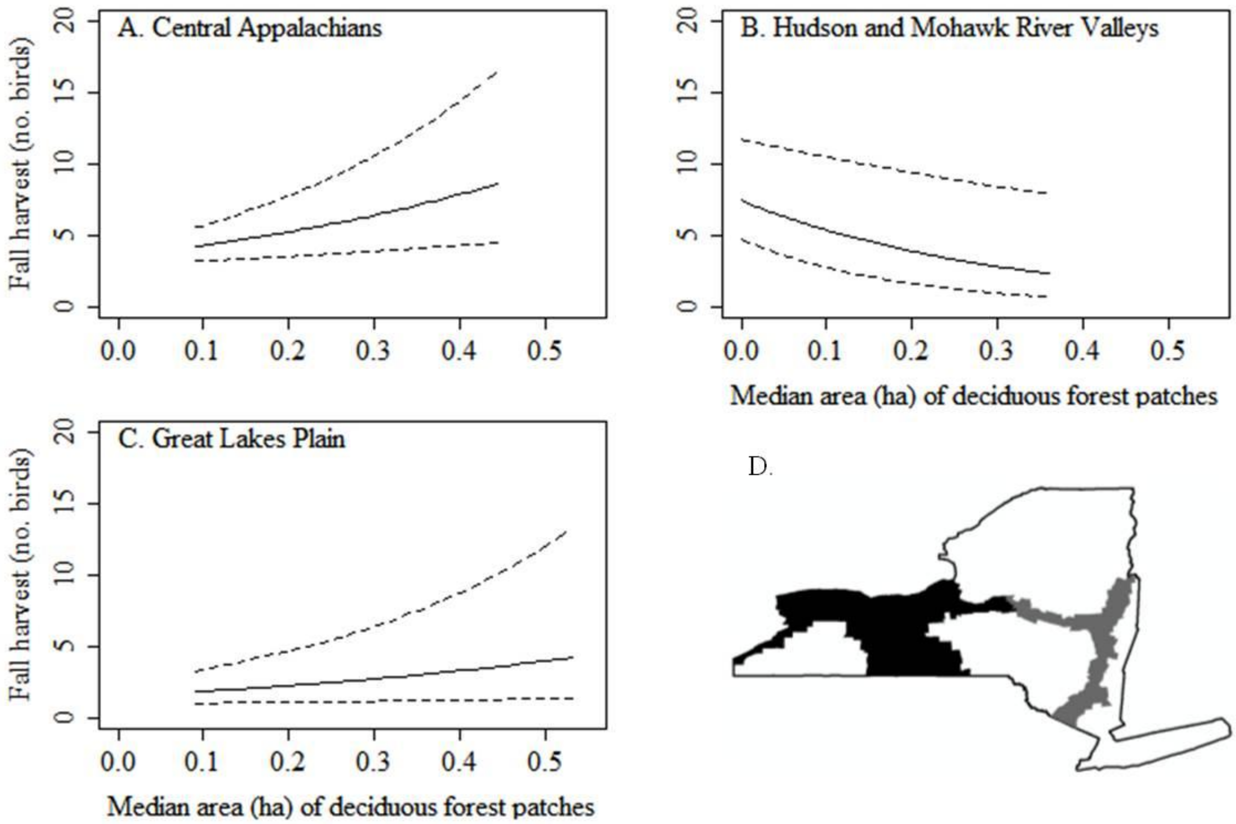

Figure C-4. The median area of deciduous forest patches effects on township-level fall wild turkey harvest (adjusted by effort) in the Central Appalachians (A), the Hudson and Mohawk River Valleys (B), and the Great Lakes Plain (C) in New York State (D) from 1984−2009 (95% confidence intervals indicated by dashed lines).

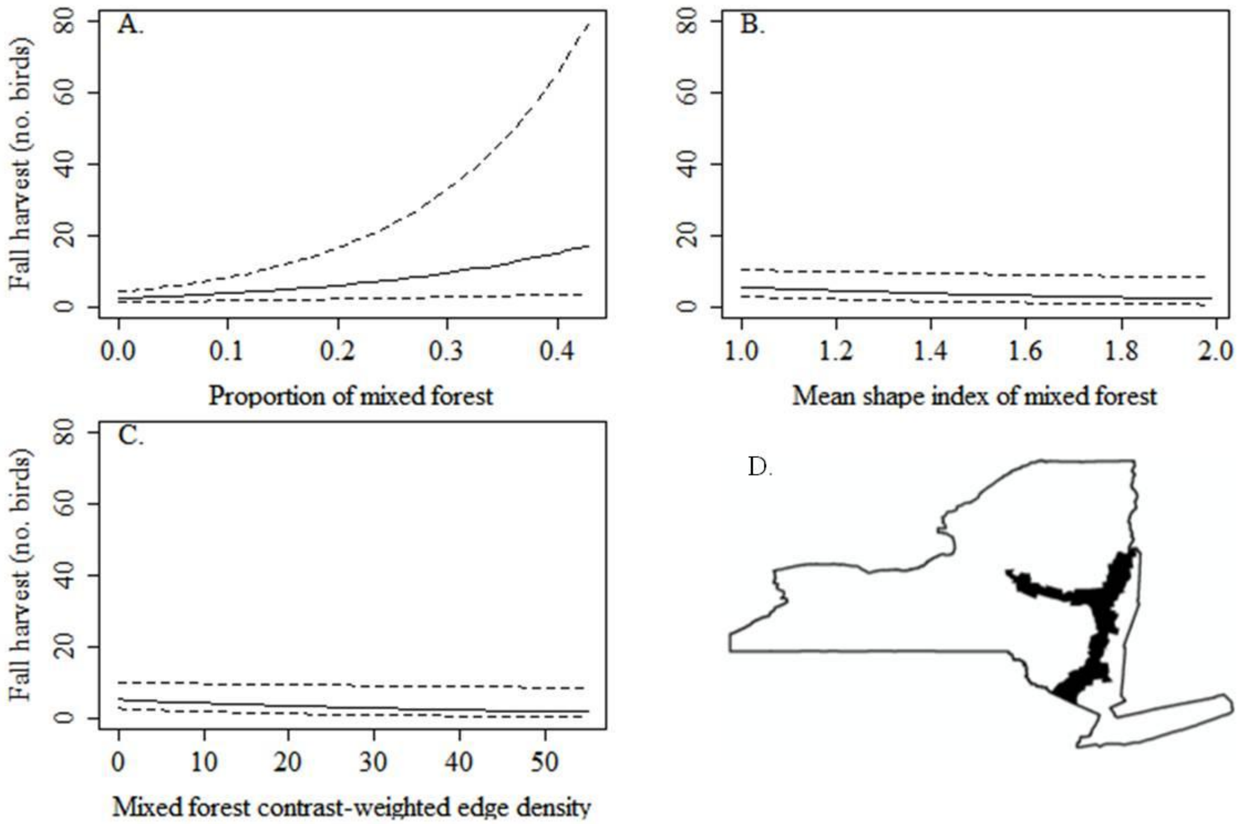

Figure C-5. Proportion of mixed forest (A), mean shape index of mixed forest patches (B), and the CWED of mixed forest (C) effects on township-level fall wild turkey harvest (adjusted by effort) in the Hudson and Mohawk River Valleys of New York State (D) from 1984–2009 (95% confidence intervals indicated by dashed lines).

APPENDIX D. REGIONAL FALL HARVEST POTENTIAL FOR WILD TURKEYS IN NEW YORK STATE.

We evaluated the regional capacities for populations to support relative levels of harvest (i.e., harvest potential) through long-term mean and variability. We delineated regional differences in the ability of populations to sustain harvest pressure using the fitted values from the top models of the 7 climate-ecozones from Chapter 1; the fitted values are referenced to township (n = 918) and year (from 1984–2009). We used the fitted values to account for the relationships between environmental variables and harvest across the landscape. This allows managers to predict harvest, and predicting mean harvest and harvest variability is essential to identify regional harvest potential and to delineate regulatory boundaries that allow for sustainable harvests.

With long-term data sets, two important metrics of harvest sustainability are the long-term mean and the variability harvest. Regions with high-quality habitat should have higher mean harvest compared with regions of poorer-quality habitat (Caughley et al. 1987). Regions with high mean harvest should also have high variability while regions with low mean harvest are predicted to fluctuate with a smaller amplitude (Gefell 1991). Those regions with high variability are likely affected by unpredictable weather (Caughley et al. 1987, Vangilder et al. 1987, Healy 1992, Palmer et al. 1993). Past research shows that mean and variation in eastern wild turkey populations is driven by spring weather and landscape-scale habitat. Chapter 1 integrated weather and habitat to quantify their effects on harvest and understand what drives harvest potential.

The relative harvest potential of a region is reflected in both mean and variability of annual fall turkey harvests. Variability was assessed with standard deviation of fitted harvest values from the top model for each climate-ecozone. We identified the pattern of the mean and standard deviation of fitted harvest from the study period for townships across New York State. Fitted fall harvest mean and standard deviation of the fitted values through time varied regionally (Fig D-1). Mean harvest and harvest variability are clustered: there are low, and more consistently low, mean harvests in the Adirondacks and Tug Hill, the St. Lawrence Plain and Champlain Valley, the Great Lakes Plain, and in portions of the Central Appalachians and Hudson and Mohawk River Valleys. There are comparatively high and variable mean harvests in the Southwest, other portions of the Central Appalachians, the Eastern Appalachians and Taconic Hills, and in other portions of the Hudson and Mohawk River Valleys.

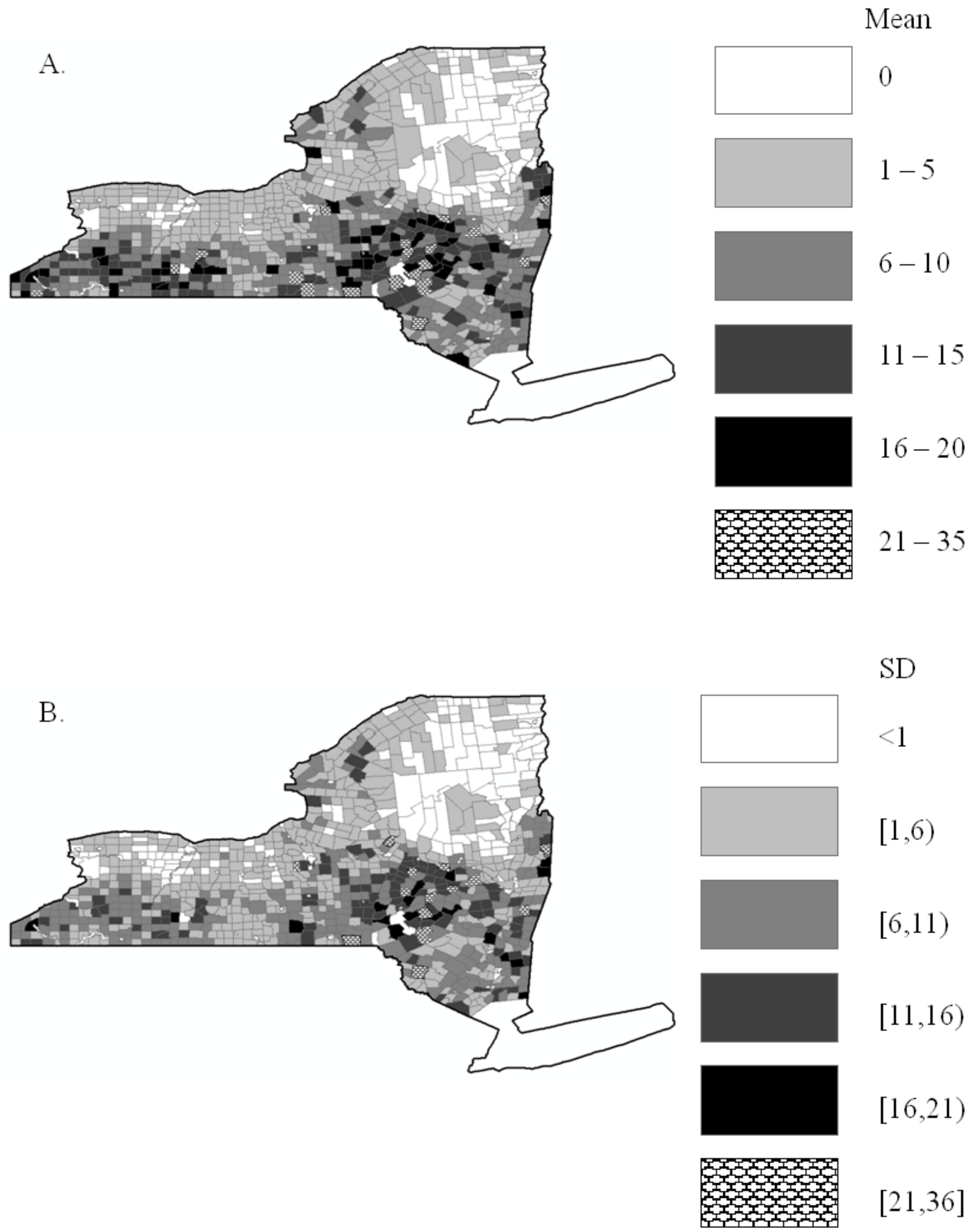

Figure D-1. Township-level means and standard deviations of fall wild turkey harvest (adjusted by effort) in New York State from 1984−2009 using the fitted values across all years for each township from the top model from each of the 7 climate-ecozones. The legend for B is written in interval form (e.g. [1, 6) reads: from 1 to 6, including 1, but excluding 6).

First, we referenced the fitted harvest values from the top models to the centroids of their respective townships and calculated the temporal mean and standard deviation. Then we used Inverse Distance Weighting (IDW) interpolation in ArcGIS 10.2 (ESRI 2014) as tool to visualize regional patterns in mean and standard deviation. IDW is an objective method for evaluating (i.e., visualizing) areal patterns, assigning values to those new locations (i.e, other than township centroids) based on surrounding measured values. This creates a smoothed summary surface of output values that are limited to the range of input values and are based on user-specified constraints (Bivand et al. 2008). To examine several scales at which the regional mean and standard deviations were similar, we ran 12 iterations of the IDW tool, representing 6 spatial scales for each of the 2 metrics. Consecutively larger numbers of points for the surface-smoothing (interpolating) calculations allows examination of the patterns at consecutively larger scales, so we used 12 (default value), 24, 48, 96, 192, and 300 points (i.e., neighboring township centroids). All other constraints were kept constant; we used the default output cell size, set the search radius at variable with no maximum distance and a power of 0.2. Fluctuations in wild turkey populations have been observed to be synchronous at < 150 km (Fleming and Porter 2007b). This distance translates to about 300 neighboring townships in southern New York State and about 200 in the northern New York State. The smaller number of neighboring townships used in the calculations returned maps with finer detail in pattern description, and larger numbers of neighboring townships allowed for larger-scaled description. The locations with the same interpolated values from the IDW have similar mean or standard deviation values. Low mean fitted fall harvest in a location translates to low harvest potential and high mean fitted fall harvest with a small standard deviation in a location translates to high harvest potential.

As an increasing number of neighboring townships are used in the IDW interpolation, an increasingly larger scale is examined, and the summary of the fitted means and standard deviation of the fitted values became increasingly smoothed (Figures D-2 and D-3). Regardless of number of neighboring townships chosen there are clearly defined mean levels of harvest with similar levels of variability (e.g. where there is a high mean harvest, there is high variability). Using 12 neighboring townships for interpolation closely resembles the township scale of fitted fall harvest mean and standard deviation values. Conversely, using 192 and 300 neighboring townships for calculations allows large-scale examination. The surface from the IDWs that incorporated 192 and 300 neighboring townships best represents the spatial scale at which wild turkey populations are known to be synchronous (< 150 km; Fleming and Porter 2007b). In the southern part of the state where the townships are smaller, and their centroids closer, the 150 km synchrony-distance includes 300 neighboring townships. In the northern part of the state where the townships are larger, and their centroids farther apart, the 150 km synchrony-distance includes 192 neighboring townships. The surfaces of the IDW using 192 versus 300 points are strikingly similar, and either choice, or a combination, is appropriate. Simultaneously examining the 300-neighboring township mean and standard deviation summary surfaces gives a large-scale view of harvest potential (Fig D-4).

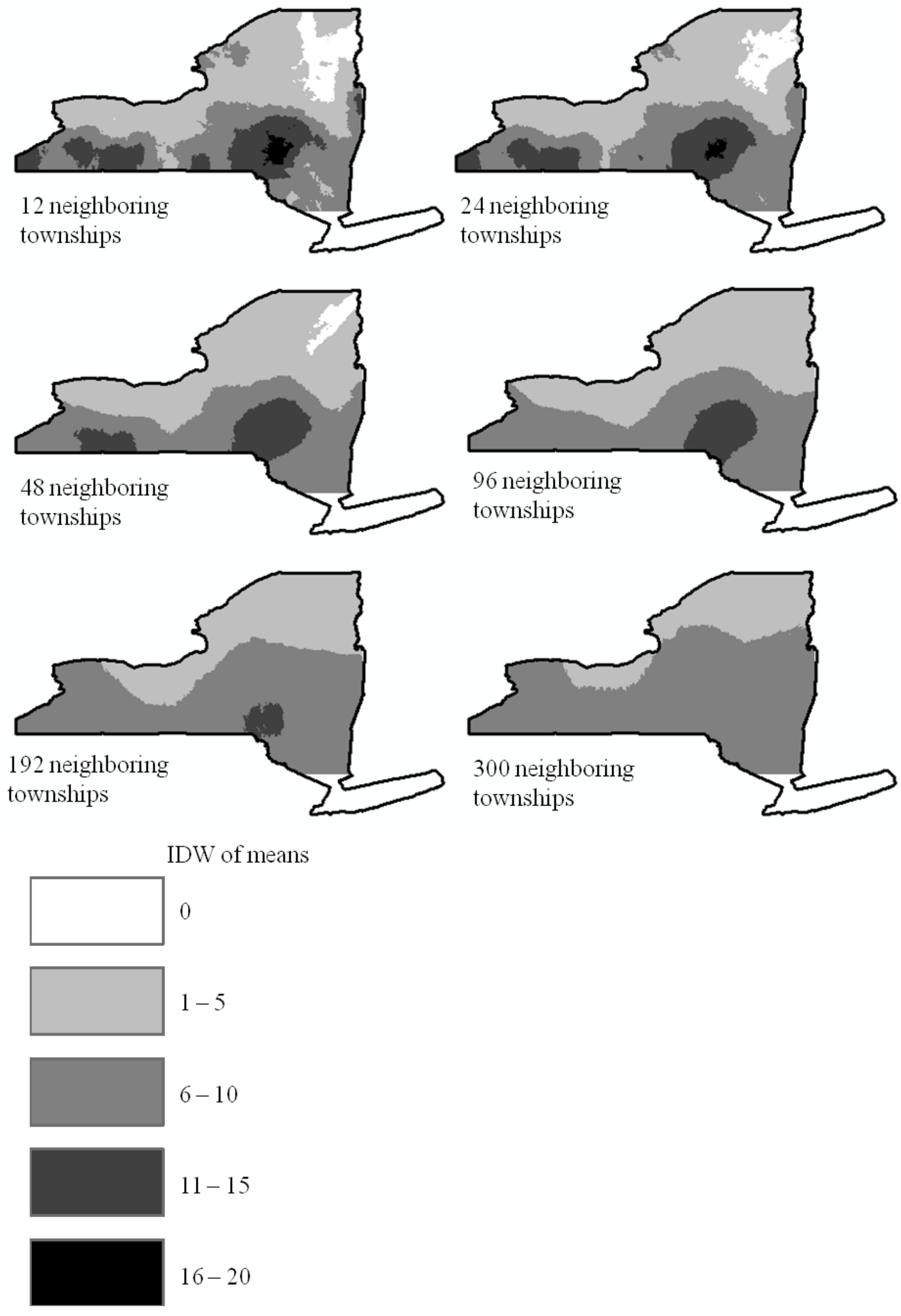

Figure D-2. Regional mean township-level fall wild turkey harvest (adjusted by effort) in New York State from 1984−2009 at increasingly larger scales using inverse distance weighting to quantify patterns of spatial clustering of township-level 26-year mean fitted harvest.

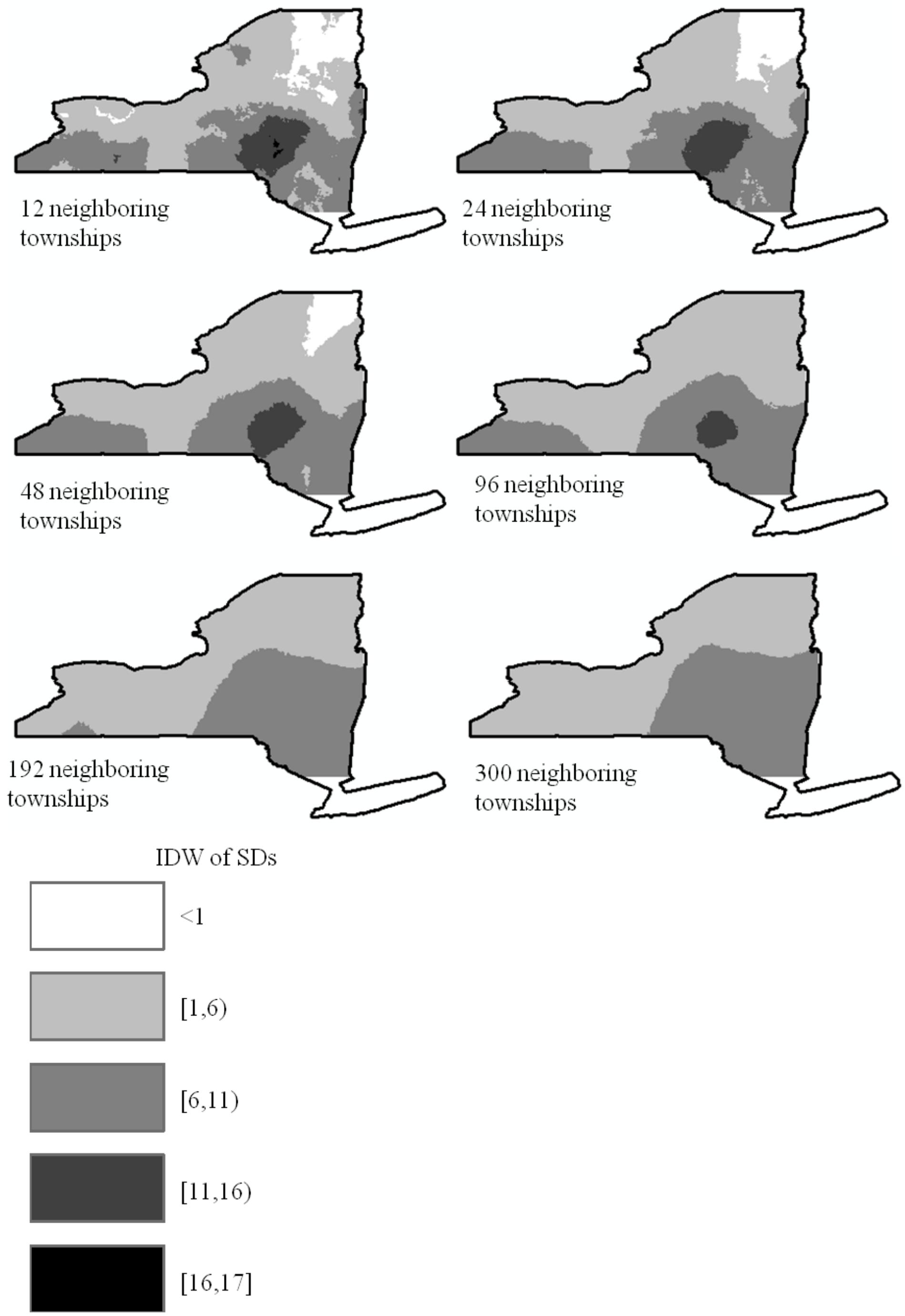

Figure D-3. Regional variability of township-level fall wild turkey harvest (adjusted by effort) in New York State from 1984−2009 at increasingly larger scales using inverse distance weighting to quantify patterns of spatial clustering of township-level 26-year standard deviation of fitted

Figure D-3 (cont'd)

harvest. The legend is written in interval form (e.g. [1, 6) reads: from 1 to 6, do include 1, but do not include 6).

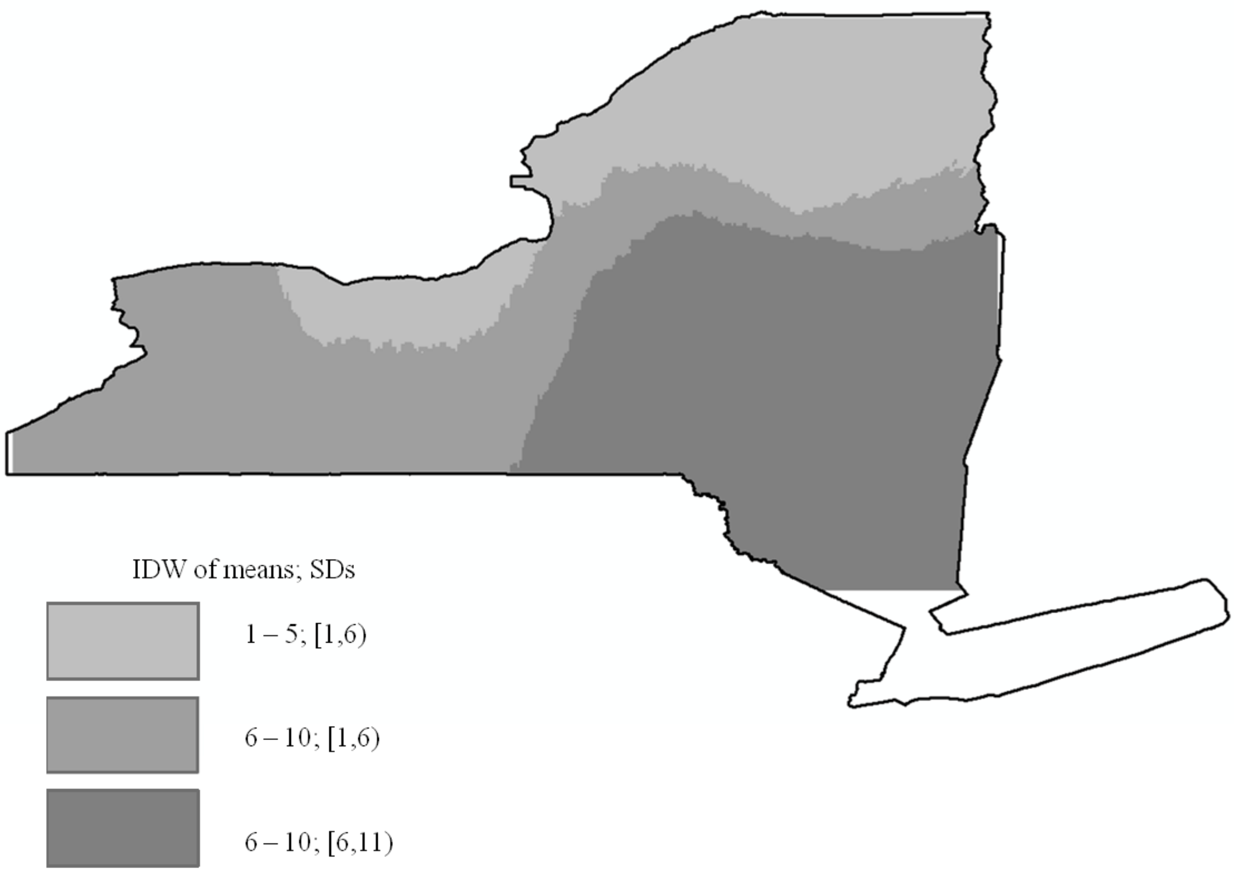

Figure D-4. Regional township-level fall wild turkey harvest potential in New York State from 1984−2009. Overlain summary surfaces of mean and standard deviation calculated by inverse distance weighting using 300 neighboring townships. The SDs in the legend are in interval form (e.g. [1, 6) reads: from 1 to 6, do include 1, but do not include 6).

Our goal was to inform managers of regional harvest potential as they re-examine fall harvest regulations. We were able to use our knowledge of the effects of environmental drivers on harvest to understand regional differences in long-term mean and variability of harvest.

When trying to understand relative harvest potential of populations, the central question follows. Does good habitat mitigate the detrimental effects of weather or does good habitat allow populations to grow large when weather conditions are ideal, but inclement weather drives population abundance down? Past studies suggest that habitat tends to drive the long-term mean because the landscape is relatively static. Conversely, weather is highly variable, and therefore more likely to drive the annual variation (Gefell 1991). We saw higher means and higher variability in areas of good habitat. The differences in how weather and habitat drive populations among climate-ecozones translate to regional harvest potential.

Regions with high mean harvest also had high variability while regions with low mean harvest fluctuated with smaller amplitude and were more stable (Gefell 1991). Regions of poorer-quality habitat had relatively lower mean harvest compared with regions of high-quality habitat (Caughley et al. 1987). In regions that have consistently (relatively small standard deviation) low mean fitted harvest (e.g., Adirondacks, St. Lawrence Plain, Champlain Valley, central Great Lakes Plain), harvest potential is low. In regions that have consistently high mean fitted harvest (e.g., the Southwest, west Great Lakes Plain, Central Appalachians, Tug Hill, and the southern Adirondacks), harvest potential is higher. In regions that are high, but have more annual variation (e.g., Eastern Appalachians, Hudson River Valley, Taconic Hills, and Mohawk River Valley), harvest potential is not as high as the consistently high regions. Those regions with high variability were also affected by unpredictable spring weather (Vangilder et al. 1987, Healy 1992, Palmer et al. 1993).

Understanding the relationships between the fundamental and context-specific variables and fall harvest help us predict harvest and harvest variability across many types of climate regions and ecoregions, thus allowing us to assess and map regional differences in long-term sustainable harvest potential. We identified regions where abundance is high and variable and where abundance is consistently low. The regional scale is not as large as the state (~140,300 km^2), but not as small as the wildlife management unit aggregation (625 – 12,558 km^2), and differences are along different delineations than harvest zones (620 – 25,433 km^2) that are currently in use.

Reworking harvest regulations more specifically to the regional potential for wild turkey populations is the most accessible tool available to managers. We have provided an understanding of the regional capacity for harvest potential to help determine new boundaries for modification of harvest zones.

APPENDIX E. FULL MODEL SELECTION TABLES FROM THE TOP MODELS FOR SPRING ABUNDANCE IN THE 7 REGIONS IN NEW YORK STATE FROM 1985−2010.

Table E-1. Model set for analysis of drivers of spring abundance of wild turkeys in southwest New York during 1985-2010. Models below are for fixed effects only. Each of the models included all the random effects and the error structure previously chosen by AIC. K is the number of parameters. w is the model weight.

Model name	ΔAIC	K	w
Y [a] + SDD [b] + Lg SDD [c] + (SDD × Lg SDD)	0	10	0.290
Y + FH [d] + SDD + Lg SDD + (SDD × Lg SDD)	1.7	11	0.126
Y + CL_PLAND [e] + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)	3	12	0.065
Y + SDD + Lg CL_PLAND [f] + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	3	12	0.064
Y + SDD + Lg SDD	3.1	9	0.060
Y + SDD + Lg SDD + (SDD × Lg SDD) + BF + JM + JAM + DFH	4.2	23	0.035
Y + SDD + Lg SDD + SDD^2 [g] + Lg SDD^2 [h]	4.3	11	0.034
Y + CL_PLAND + SDD + Lg SDD	4.4	10	0.032
Y + FH + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)	4.7	13	0.028
Y + FH + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	4.7	13	0.028
Y + FH + SDD + Lg SDD	4.9	10	0.025
Y + FH + SDD + Lg SDD + SDD^2 + Lg SDD^2	6	12	0.015
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)	6	11	0.014
Y + FH + CL_PLAND + SDD + Lg SDD	6.2	11	0.013

Table E-1 (cont'd)

Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	6.3	11	0.012
Y + Lg SDD + Lg SDD^2	7.3	9	0.008
Y + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 [i] + SDD^2 + Lg SDD^2	7.6	13	0.006
Y + Lg SDD	7.6	8	0.006
Y + FH + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)	7.8	12	0.006
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD) + BF [j] + JM [k] + JAM [l] + DFH [m]	7.9	25	0.006
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD) + BF + JM + JAM + DFH	8.1	25	0.005
Y + FH + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	8.1	12	0.005
Y + SDD + Lg SDD + BF + JM + JAM + DFH	8.3	22	0.005
Y + SDD + Lg SDD + SDD^2 + Lg SDD^2 + BF + JM + JAM + DFH	8.4	24	0.004
Y + CL_PLAND + Lg SDD	8.6	9	0.004
Y + FH + Lg SDD + Lg SDD^2	9.2	10	0.003
Y + FH + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2	9.3	14	0.003
Y + FH + Lg SDD	9.5	9	0.002
Y + CL_PLAND + SDD + Lg SDD + BF + JM + JAM + DFH	10.2	23	0.002
Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2	10.2	11	0.002
Y + FH + Lg CL_PLAND + SDD + Lg SDD + Lg CL_PLAND^2 [n] + SDD^2 + Lg SDD^2 + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	10.4	16	0.002

Table E-1 (cont'd)

Y + FH + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2 + (CL_PLAND × SDD) + (SDD × Lg SDD)	10.4	16	0.002
Y + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	10.5	10	0.002
Y + FH + CL_PLAND + Lg SDD	10.5	10	0.002
Y + SDD	10.7	8	0.001
Y + Lg SDD + Lg SDD^2 + BF + JM + JAM + DFH	10.8	22	0.001
Y + SDD + SDD^2	11.1	9	0.001
Y + CL_PLAND	11.2	8	0.001
Y + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2 + BF + JM + JAM + DFH	11.4	26	< 0.001
Y + FH	11.8	8	< 0.001
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + BF + JM + JAM + DFH	12	24	< 0.001
Y + CL_PLAND + SDD	12	9	< 0.001
Y + FH + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2	12	12	< 0.001
Y + Lg SDD + BF + JM + JAM + DFH	12.1	21	< 0.001
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH	12.2	24	< 0.001
Y + FH + SDD	12.3	9	< 0.001
Y + FH + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	12.4	11	< 0.001
Y + FH + SDD + SDD^2	12.8	10	< 0.001
Y + FH + CL_PLAND	12.9	9	< 0.001

Table E-1 (cont'd)

Y + CL_PLAND + CL_PLAND^2	13.2	9	< 0.001
Y + CL_PLAND + SDD + (CL_PLAND × SDD)	13.2	10	< 0.001
Y + FH + CL_PLAND + SDD	13.6	10	< 0.001
Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2 + BF + JM + JAM + DFH	13.9	24	< 0.001
Y + FH + Lg CL_PLAND + Lg SDD + Lg CL_PLAND^2 + Lg SDD^2 + (Lg CL_PLAND × Lg SDD)	14	13	< 0.001
Y + CL_PLAND + Lg SDD + BF + JM + JAM + DFH	14.1	22	< 0.001
Y + CL_PLAND + SDD + CL_PLAND^2 + SDD^2	14.4	11	< 0.001
Y + FH + CL_PLAND + SDD + (CL_PLAND × SDD)	14.8	11	< 0.001
Y + FH + CL_PLAND + CL_PLAND^2	14.9	10	< 0.001
Y + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH	16.1	23	< 0.001
Y + FH + CL_PLAND + SDD + CL_PLAND^2 + SDD^2	16.1	12	< 0.001
Y + SDD + SDD^2 + BF + JM + JAM + DFH	17.4	22	< 0.001
Y + SDD + BF + JM + JAM + DFH	17.5	21	< 0.001
Y + CL_PLAND + BF + JM + JAM + DFH	18.3	21	< 0.001
Y + CL_PLAND + SDD + BF + JM + JAM + DFH	19.3	22	< 0.001
Y + CL_PLAND + CL_PLAND^2 + BF + JM + JAM + DFH	19.4	22	< 0.001
Y + CL_PLAND + SDD + CL_PLAND^2 + SDD^2 + BF + JM + JAM + DFH	20.3	24	< 0.001
Y + CL_PLAND + SDD + (CL_PLAND × SDD) + BF + JM + JAM + DFH	20.8	23	< 0.001

Table E-1 (cont'd)

Y [a]: Yr

SDD [b]: Snow depth days (i.e., winter severity) from immediately preceding winter

Lg SDD [c]: Year lag of winter severity (i.e., snow depth days from 2 winters previous)

FH [d]: Total fall harvest from the previous calendar year

CL_PLAND [e]: Proportion of cultivated land

Lg CL_PLAND [f]: Proportion of cultivated land from 2 winters previous

SDD^2 [g]: Snow depth days ^{2}

Lg SDD^2 [h]: Snow depth days from 2 winters previous ^{2}

CL_PLAND^2 [i]: Proportion of cultivated land ^{2}

BF [j]: Brood flock count from preceding August

JM [k]: Total juvenile males in current spring harvest

JAM [l]: Ratio of juvenile males to adult males in current spring harvest

DFH [m]: Drivers of fall harvest: June rainfall + Landscape-level edge density + Landscape-level edge density ^{2} + Proportion of evergreen forest + Proportion of evergreen forest ^{2} + Proportion of mixed forest + CV of deciduous forest patch areas + Median patch area of evergreen forest + CV of evergreen forest patch areas + Median patch area of mixed forest

Lg CL_PLAND^2 [n]: Proportion of cultivated land from 2 winters previous ^{2}

Table E-2. Model set for analysis of drivers of spring abundance of wild turkeys in the Central Appalachians of New York during 1985-2010. Models below are for fixed effects only. Each of the models included all the random effects and the error structure previously chosen by AIC. K is the number of parameters. w is the model weight.

Model name	ΔAIC	K	w
Y [a] + CL_PLAND [b] + CL_PLAND^2 [c]	0	9	0.060
Y + SDD [d] + Lg SDD [e] + (SDD × Lg SDD)	0.3	10	0.051
Y + Lg SDD	0.4	8	0.049
Y + CL_PLAND + CL_PLAND^2 + BF [f] + JM [g] + JAM [h] + DFH [i]	0.7	21	0.042
Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2 [j]	1.2	11	0.033
Y + SDD + Lg SDD	1.4	9	0.030
Y + CL_PLAND + Lg SDD	1.7	9	0.025
Y + Lg SDD + Lg SDD^2	1.8	9	0.025
Y + FH [k] + CL_PLAND + CL_PLAND^2	1.9	10	0.023
Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2 + BF + JM + JAM + DFH	1.9	23	0.023
Y + CL_PLAND	2	8	0.022
Y + SDD	2.1	8	0.021
Y + FH + SDD + Lg SDD + (SDD × Lg SDD)	2.1	11	0.021
Y + Lg SDD + BF + JM + JAM + DFH	2.2	20	0.020
Y + FH + Lg SDD	2.2	9	0.020
Y + FH	2.3	8	0.019

Table E-2 (cont’d)

Y + CL_PLAND + SDD + Lg SDD	2.8	10	0.015
Y + SDD + Lg SDD + (SDD × Lg SDD) + BF + JM + JAM + DFH	3.1	22	0.013
Y + FH + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2	3.1	12	0.013
Y + CL_PLAND + Lg SDD + BF + JM + JAM + DFH	3.1	21	0.013
Y + FH + SDD + Lg SDD	3.1	10	0.013
Y + SDD + Lg CL_PLAND [l] + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	3.4	12	0.011
Y + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	3.4	10	0.011
Y + CL_PLAND + SDD + CL_PLAND^2 + SDD^2 [m]	3.5	11	0.010
Y + FH + CL_PLAND + Lg SDD	3.5	10	0.010
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)	3.6	12	0.010
Y + FH + Lg SDD + Lg SDD^2	3.6	10	0.010
Y + CL_PLAND + SDD	3.8	9	0.009
Y + FH + CL_PLAND	3.8	9	0.009
Y + CL_PLAND + BF + JM + JAM + DFH	3.8	20	0.009
Y + FH + SDD	3.8	9	0.009
Y + SDD + SDD^2	4	9	0.008
Y + Lg SDD + Lg SDD^2 + BF + JM + JAM + DFH	4.1	21	0.008
Y + SDD + Lg SDD + BF + JM + JAM + DFH	4.2	21	0.008
Y + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2	4.2	13	0.007

Table E-2 (cont'd)

Y + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH	4.5	22	0.006
Y + FH + CL_PLAND + SDD + Lg SDD	4.6	11	0.006
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	4.6	11	0.006
Y + CL_PLAND + SDD + CL_PLAND^2 + SDD^2 + BF + JM + JAM + DFH	4.7	23	0.006
Y + SDD + BF + JM + JAM + DFH	4.8	20	0.006
Y + SDD + Lg SDD + SDD^2 + Lg SDD^2	4.8	11	0.006
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)	4.8	11	0.005
Y + CL_PLAND + SDD + Lg SDD + BF + JM + JAM + DFH	5.1	22	0.005
Y + FH + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	5.2	13	0.004
Y + FH + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	5.2	11	0.004
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD) + BF + JM + JAM + DFH	5.3	24	0.004
Y + FH + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)	5.4	13	0.004
Y + FH + CL_PLAND + SDD + CL_PLAND^2 + SDD^2	5.4	12	0.004
Y + FH + CL_PLAND + SDD	5.5	10	0.004
Y + CL_PLAND + SDD + (CL_PLAND × SDD)	5.6	10	0.004
Y + FH + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2 + (CL_PLAND × SDD) + (SDD × Lg SDD)	5.6	16	0.004
Y + FH + SDD + SDD^2	5.7	10	0.003

Table E-2 (cont'd)

Y + CL_PLAND + SDD + BF + JM + JAM + DFH	5.8	21	0.003
Y + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2 + BF + JM + JAM + DFH	5.8	25	0.003
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD) + BF + JM + JAM + DFH	6	24	0.003
Y + FH + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2	6.1	14	0.003
Y + FH + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	6.3	12	0.003
Y + FH + Lg CL_PLAND + Lg SDD + Lg CL_PLAND$^{2\,n}$ + Lg SDD^2 + (Lg CL_PLAND × Lg SDD)	6.4	13	0.002
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH	6.5	23	0.002
Y + FH + SDD + Lg SDD + SDD^2 + Lg SDD^2	6.5	12	0.002
Y + FH + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)	6.6	12	0.002
Y + SDD + SDD^2 + BF + JM + JAM + DFH	6.7	21	0.002
Y + FH + Lg CL_PLAND + SDD + Lg SDD + Lg CL_PLAND^2 + SDD^2 + Lg SDD^2 + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	7	16	0.002
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + BF + JM + JAM + DFH	7	23	0.002
Y + FH + CL_PLAND + SDD + (CL_PLAND × SDD)	7.3	11	0.002
Y + CL_PLAND + SDD + (CL_PLAND × SDD) + BF + JM + JAM + DFH	7.8	22	0.001
Y + SDD + Lg SDD + SDD^2 + Lg SDD^2 + BF + JM + JAM + DFH	8	23	0.001

Table E-2 (cont'd)

Y [a]:	Yr
CL_PLAND [b]:	Proportion of cultivated land
CL_PLAND^2 [c]:	Proportion of cultivated land ^{2}
SDD [d]:	Snow depth days (i.e., winter severity) from immediately preceding winter
Lg SDD [e]:	Year lag of winter severity (i.e., snow depth days from 2 winters previous)
BF [f]:	Brood flock count from preceding August
JM [g]:	Total juvenile males in current spring harvest
JAM [h]:	Ratio of juvenile males to adult males in current spring harvest
DFH [i]:	Drivers of fall harvest: May rainfall + Landscape-level edge density + Landscape-level contrast-weighted edge density + Landscape-level contrast-weighted edge density ^{2} + Proportion of open lands + Proportion of forest lands + Proportion of forest lands ^{2} + Contrast-weighted edge density of evergreen forest + Median patch area of deciduous forest
Lg SDD^2 [j]:	Snow depth days from 2 winters previous ^{2}
FH [k]:	Total fall harvest from the previous calendar year
Lg CL_PLAND [l]:	Proportion of cultivated land from 2 winters previous
SDD^2 [m]:	Snow depth days ^{2}
Lg CL_PLAND^2 [n]:	Proportion of cultivated land from 2 winters previous ^{2}

Table E-3. Model set for analysis of drivers of spring abundance of wild turkeys in the Eastern Appalachians and Taconic Hills of New York during 1985-2010. Models below are for fixed effects only. Each of the models included all the random effects and the error structure previously chosen by AIC. K is the number of parameters. w is the model weight.

Model name	ΔAIC	K	w
Y [a] + FH [b] + CL_PLAND [c] + SDD [d] + (CL_PLAND × SDD)	0	10	0.183
Y + FH + CL_PLAND + SDD + CL_PLAND^2 [e] + SDD^2 [f]	1	11	0.111
Y + CL_PLAND + SDD + (CL_PLAND × SDD)	1.4	9	0.091
Y + FH + CL_PLAND + SDD + Lg SDD [g] + CL_PLAND^2 + SDD^2 + Lg SDD^2 [h] + (CL_PLAND × SDD) + (SDD × Lg SDD)	1.6	15	0.082
Y + FH + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)	2	11	0.067
Y + FH + CL_PLAND + CL_PLAND^2	2.2	9	0.061
Y + CL_PLAND + SDD + CL_PLAND^2 + SDD^2	2.4	10	0.055
Y + CL_PLAND + CL_PLAND^2	3.2	8	0.037
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)	3.4	10	0.034
Y + FH + CL_PLAND + SDD	4.2	9	0.022
Y + FH + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2	4.6	13	0.018
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)	4.8	11	0.017
Y + CL_PLAND + SDD	5	8	0.015
Y + FH + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2	5.4	11	0.012
Y + FH + CL_PLAND + SDD + Lg SDD	6.2	10	0.008
Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2	6.6	10	0.007

Table E-3 (cont'd)

Y + CL_PLAND + SDD + Lg SDD	7	9	0.006
Y + FH + SDD + Lg CL_PLAND [i] + Lg SDD + (Lg CL_PLAND × Lg SDD)	7.2	11	0.005
Y + FH + Lg CL_PLAND + Lg SDD + Lg CL_PLAND^2 [j] + Lg SDD^2 + (Lg CL_PLAND × Lg SDD)	7.8	12	0.004
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	8	10	0.003
Y + FH + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	9.2	12	0.002
Y + FH + SDD	9.2	8	0.002
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	10	11	0.001
Y + FH + CL_PLAND	10	8	0.001
Y + CL_PLAND	10	7	0.001
Y + SDD	10	7	0.001
Y + FH + SDD + Lg SDD	11	9	< 0.001
Y + FH + SDD + SDD^2	11	9	< 0.001
Y + FH + CL_PLAND + Lg SDD	11	9	< 0.001
Y + CL_PLAND + Lg SDD	12	8	< 0.001
Y + SDD + Lg SDD	12	8	< 0.001
Y + SDD + SDD^2	12	8	< 0.001
Y + FH + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	12	10	< 0.001
Y + FH + SDD + Lg SDD + (SDD × Lg SDD)	13	10	< 0.001

Table E-3 (cont'd)

Y + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	13	9	< 0.001
Y + SDD + Lg SDD + (SDD × Lg SDD)	14	9	< 0.001
Y + FH + SDD + Lg SDD + SDD^2 + Lg SDD^2	14	11	< 0.001
Y + SDD + Lg SDD + SDD^2 + Lg SDD^2	16	10	< 0.001
Y + CL_PLAND + SDD + (CL_PLAND × SDD) + BF [k] + JM [l] + JAM [m] + DFH [n]	17	28	< 0.001
Y + FH + Lg SDD	19	8	< 0.001
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + BF + JM + JAM + DFH	19	29	< 0.001
Y + FH	19	7	< 0.001
Y + FH + Lg SDD + Lg SDD^2	20	9	< 0.001
Y + Lg SDD	20	7	< 0.001
Y + SDD + BF + JM + JAM + DFH	20	26	< 0.001
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD) + BF + JM + JAM + DFH	21	30	< 0.001
Y + CL_PLAND + SDD + BF + JM + JAM + DFH	21	27	< 0.001
Y + Lg SDD + Lg SDD^2	21	8	< 0.001
Y + SDD + SDD^2 + BF + JM + JAM + DFH	22	27	< 0.001
Y + SDD + Lg SDD + BF + JM + JAM + DFH	22	27	< 0.001
Y + CL_PLAND + SDD + Lg SDD + BF + JM + JAM + DFH	23	28	< 0.001
Y + CL_PLAND + SDD + CL_PLAND^2 + SDD^2 + BF + JM + JAM + DFH	24	29	< 0.001

Table E-3 (cont'd)

Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH	24	29	< 0.001
Y + CL_PLAND + BF + JM + JAM + DFH	24	26	< 0.001
Y + CL_PLAND + CL_PLAND^2 + BF + JM + JAM + DFH	24	27	< 0.001
Y + SDD + Lg SDD + (SDD × Lg SDD) + BF + JM + JAM + DFH	24	28	< 0.001
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD) + BF + JM + JAM + DFH	25	30	< 0.001
Y + CL_PLAND + Lg SDD + BF + JM + JAM + DFH	26	27	< 0.001
Y + SDD + Lg SDD + SDD^2 + Lg SDD^2 + BF + JM + JAM + DFH	26	29	< 0.001
Y + Lg SDD + BF + JM + JAM + DFH	26	26	< 0.001
Y + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH	27	28	< 0.001
Y + Lg SDD + Lg SDD^2 + BF + JM + JAM + DFH	27	27	< 0.001
Y + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2 + BF + JM + JAM + DFH	27	31	< 0.001
Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2 + BF + JM + JAM + DFH	27	29	< 0.001

Y [a]: Yr

FH [b]: Total fall harvest from the previous calendar year

CL_PLAND [c]: Proportion of cultivated land

SDD [d]: Snow depth days (i.e., winter severity) from immediately preceding winter

CL_PLAND^2 [e]: Proportion of cultivated land ^{2}

SDD^2 [f]: Snow depth days ^{2}

Lg SDD [g]: Year lag of winter severity (i.e., snow depth days from 2 winters previous)

Table E-3 (cont'd)

Lg SDD^{2} [h]: Snow depth days from 2 winters previous ^{2}

Lg CL_PLAND [i]: Proportion of cultivated land from 2 winters previous

Lg CL_PLAND^{2} [j]: Proportion of cultivated land from 2 winters previous ^{2}

BF [k]: Brood flock count from preceding August

JM [l]: Total juvenile males in current spring harvest

JAM [m]: Ratio of juvenile males to adult males in current spring harvest

DFH [n]: Drivers of fall harvest: May rainfall + June rainfall + Landscape-level edge density + Landscape-level edge density ^{2} + Landscape-level contrast-weighted edge density + Landscape-level contrast-weighted edge density ^{2} + Interspersion and juxtaposition + Proportion of open lands + Proportion of open lands^{2} + Contrast-weighted edge density of evergreen forest + Evergreen forest mean shape index + Median patch area of evergreen forest + (May rainfall × Contrast-weighted edge density of evergreen forest) + (May rainfall × Interspersion and juxtaposition) + (June rainfall × Proportion of open lands) + (June rainfall × Interspersion and juxtaposition)

Table E-4. Model set for analysis of drivers of spring abundance of wild turkeys in the Hudson and Mohawk River Valleys of New York during 1985-2010. Models below are for fixed effects only. Each of the models included all the random effects and the error structure previously chosen by AIC. K is the number of parameters. w is the model weight.

Model name	ΔAIC	K	w
Y [a] + SDD [b] + SDD^2 [c]	0	8	0.223
Y + FH [d] + SDD + SDD^2	1.4	9	0.110
Y + SDD + Lg SDD [e] + SDD^2 + Lg SDD^2 [f]	3.2	10	0.046
Y + CL_PLAND [g] + SDD + CL_PLAND^2 [h] + SDD^2	3.5	10	0.040
Y + SDD	3.5	7	0.039
Y + FH	3.8	7	0.033
Y + CL_PLAND	4.2	7	0.027
Y + CL_PLAND + SDD + (CL_PLAND × SDD)	4.3	9	0.026
Y + Lg SDD	4.4	7	0.024
Y + FH + SDD + Lg SDD + SDD^2 + Lg SDD^2	4.6	11	0.022
Y + FH + CL_PLAND + SDD + CL_PLAND^2 + SDD^2	4.7	11	0.021
Y + FH + SDD	4.9	8	0.019
Y + CL_PLAND + SDD	5	8	0.018
Y + Lg SDD + Lg SDD^2	5.3	8	0.016
Y + SDD + Lg SDD	5.3	8	0.016
Y + FH + CL_PLAND + SDD + (CL_PLAND × SDD)	5.4	10	0.015
Y + FH + CL_PLAND	5.5	8	0.014

Table E-4 (cont'd)

Y + FH + Lg SDD	5.8	8	0.012
Y + CL_PLAND + CL_PLAND^2	5.9	8	0.012
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)	6.2	10	0.010
Y + CL_PLAND + Lg SDD	6.2	8	0.010
Y + FH + CL_PLAND + SDD	6.3	9	0.010
Y + FH + SDD + Lg SDD	6.7	9	0.008
Y + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2	6.7	12	0.008
Y + FH + Lg SDD + Lg SDD^2	6.8	9	0.008
Y + SDD + Lg SDD + (SDD × Lg SDD)	6.9	9	0.007
Y + CL_PLAND + SDD + Lg SDD	6.9	9	0.007
Y + FH + CL_PLAND + CL_PLAND^2	7.1	9	0.006
Y + FH + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)	7.2	11	0.006
Y + Lg CL_PLAND [i] + Lg SDD + (Lg CL_PLAND × Lg SDD)	7.3	9	0.006
Y + FH + CL_PLAND + Lg SDD	7.5	9	0.005
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	8	10	0.004
Y + FH + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2	8	13	0.004
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)	8.1	11	0.004
Y + FH + CL_PLAND + SDD + Lg SDD	8.1	10	0.004
Y + FH + SDD + Lg SDD + (SDD × Lg SDD)	8.3	10	0.004

Table E-4 (cont'd)

Y + FH + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	8.6	10	0.003
Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2	8.7	10	0.003
Y + FH + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)	9.2	12	0.002
Y + FH + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	9.2	11	0.002
Y + FH + Lg CL_PLAND + SDD + Lg SDD + Lg CL_PLAND^2 [j] + SDD^2 + Lg SDD^2 + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	9.2	15	0.002
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	9.4	11	0.002
Y + FH + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2 + (CL_PLAND × SDD) + (SDD × Lg SDD)	9.4	15	0.002
Y + FH + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2	10	11	0.001
Y + FH + Lg CL_PLAND + Lg SDD + Lg CL_PLAND^2 + Lg SDD^2 + (Lg CL_PLAND × Lg SDD)	10	12	0.001
Y + FH + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	11	12	0.001
Y + SDD + SDD^2 + BF [k] + JM [l] + JAM [m] + DFH [n]	18	21	< 0.001
Y + SDD + BF + JM + JAM + DFH	21	20	< 0.001
Y + CL_PLAND + SDD + CL_PLAND^2 + SDD^2 + BF + JM + JAM + DFH	21	23	< 0.001
Y + CL_PLAND + BF + JM + JAM + DFH	21	20	< 0.001
Y + SDD + Lg SDD + SDD^2 + Lg SDD^2 + BF + JM + JAM + DFH	22	23	< 0.001
Y + Lg SDD + BF + JM + JAM + DFH	22	20	< 0.001

Table E-4 (cont'd)

Y + CL_PLAND + SDD + (CL_PLAND × SDD) + BF + JM + JAM + DFH	22	22	< 0.001
Y + CL_PLAND + SDD + BF + JM + JAM + DFH	22	21	< 0.001
Y + SDD + Lg SDD + BF + JM + JAM + DFH	23	21	< 0.001
Y + Lg SDD + Lg SDD^2 + BF + JM + JAM + DFH	23	21	< 0.001
Y + CL_PLAND + CL_PLAND^2 + BF + JM + JAM + DFH	23	21	< 0.001
Y + CL_PLAND + Lg SDD + BF + JM + JAM + DFH	23	21	< 0.001
Y + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH	24	22	< 0.001
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + BF + JM + JAM + DFH	24	23	< 0.001
Y + CL_PLAND + SDD + Lg SDD + BF + JM + JAM + DFH	24	22	< 0.001
Y + SDD + Lg SDD + (SDD × Lg SDD) + BF + JM + JAM + DFH	24	22	< 0.001
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH	25	23	< 0.001
Y + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2 + BF + JM + JAM + DFH	25	25	< 0.001
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD) + BF + JM + JAM + DFH	26	24	< 0.001
Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2 + BF + JM + JAM + DFH	26	23	< 0.001
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD) + BF + JM + JAM + DFH	27	24	< 0.001

Y [a]: Yr

SDD [b]: Snow depth days (i.e., winter severity) from immediately preceding winter

Table E-4 (cont'd)

SDD^2 [c]: Snow depth days ^{2}

FH [d]: Total fall harvest from the previous calendar year

Lg SDD [e]: Year lag of winter severity (i.e., snow depth days from 2 winters previous)

Lg SDD^2 [f]: Snow depth days from 2 winters previous ^{2}

CL_PLAND [g]: Proportion of cultivated land

CL_PLAND^2 [h]: Proportion of cultivated land ^{2}

Lg CL_PLAND [i]: Proportion of cultivated land from 2 winters previous

Lg CL_PLAND^2 [j]: Proportion of cultivated land from 2 winters previous ^{2}

BF [k]: Brood flock count from preceding August

JM [l]: Total juvenile males in current spring harvest

JAM [m]: Ratio of juvenile males to adult males in current spring harvest

DFH [n]: Drivers of fall harvest: May rainfall + Proportion of pasture and hay + Proportion of grassland + Proportion of deciduous forest + Proportion of evergreen forest + Proportion of evergreen forest ^{2} + Proportion of mixed forest + Contrast-weighted edge density of mixed forest + Mixed forest mean shape index + Median patch area of deciduous forest

Table E-5. Model set for analysis of drivers of spring abundance of wild turkeys the Great Lakes Plain of New York during 1985-2010. Models below are for fixed effects only. Each of the models included all the random effects and the error structure previously chosen by AIC. K is the number of parameters. w is the model weight.

Model name	ΔAIC	K	w
Y [a] + CL_PLAND [b] + SDD [c] + CL_PLAND^2 [d] + SDD^2 [e]	0	11	0.063
Y + CL_PLAND + CL_PLAND^2	0.6	9	0.046
Y + CL_PLAND	0.7	8	0.045
Y + CL_PLAND + SDD	0.9	9	0.040
Y + SDD + SDD^2	1	9	0.038
Y + SDD	1.3	8	0.034
Y + FH [f] + CL_PLAND + SDD + CL_PLAND^2 + SDD^2	1.4	12	0.031
Y + CL_PLAND + Lg SDD	1.6	9	0.029
Y + SDD + Lg SDD [g] + (SDD × Lg SDD)	1.9	10	0.024
Y + CL_PLAND + SDD + (CL_PLAND × SDD)	1.9	10	0.024
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)	2	12	0.023
Y + FH + CL_PLAND + CL_PLAND^2	2.1	10	0.022
Y + Lg SDD	2.1	8	0.022
Y + FH + CL_PLAND	2.3	9	0.020
Y + FH + CL_PLAND + SDD	2.6	10	0.018
Y + Lg CL_PLAND [h] + Lg SDD + (Lg CL_PLAND × Lg SDD)	2.6	10	0.018

Table E-5 (cont'd)

Y + CL_PLAND + SDD + Lg SDD	2.7	10	0.017
Y + SDD + Lg SDD	2.8	9	0.015
Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2 [i]	2.9	11	0.015
Y + FH + SDD + SDD^2	2.9	10	0.015
Y + FH + SDD	3.1	9	0.013
Y + FH + CL_PLAND + Lg SDD	3.2	10	0.013
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	3.3	12	0.012
Y + FH + CL_PLAND + SDD + (CL_PLAND × SDD)	3.6	11	0.011
Y + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2	3.6	13	0.011
Y + FH + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)	3.7	13	0.010
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)	3.7	11	0.010
Y + FH + SDD + Lg SDD + (SDD × Lg SDD)	3.8	11	0.010
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	3.8	11	0.010
Y + Lg SDD + Lg SDD^2	3.8	9	0.009
Y + FH	3.9	8	0.009
Y + FH + Lg SDD	4	9	0.009
Y + FH + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	4.2	11	0.008
Y + FH + CL_PLAND + SDD + Lg SDD	4.3	11	0.007
Y + FH + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2	4.4	12	0.007

Table E-5 (cont'd)

Y + SDD + Lg SDD + SDD^2 + Lg SDD^2	4.6	11	0.006
Y + FH + SDD + Lg SDD	4.7	10	0.006
Y + FH + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2 + (CL_PLAND × SDD) + (SDD × Lg SDD)	4.9	16	0.005
Y + FH + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	4.9	13	0.005
Y + FH + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2	5	14	0.005
Y + FH + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)	5.3	12	0.004
Y + FH + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	5.4	12	0.004
Y + FH + Lg CL_PLAND + Lg SDD + Lg CL_PLAND^2 [j] + Lg SDD^2 + (Lg CL_PLAND × Lg SDD)	5.5	13	0.004
Y + FH + Lg SDD + Lg SDD^2	5.7	10	0.004
Y + FH + SDD + Lg SDD + SDD^2 + Lg SDD^2	6.4	12	0.003
Y + FH + Lg CL_PLAND + SDD + Lg SDD + Lg CL_PLAND^2 + SDD^2 + Lg SDD^2 + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	7.1	16	0.002
Y + CL_PLAND + CL_PLAND^2 + BF [k] + JM [l] + JAM [m] + DFH [n]	13	19	< 0.001
Y + SDD + SDD^2 + BF + JM + JAM + DFH	13	19	< 0.001
Y + SDD + BF + JM + JAM + DFH	13	18	< 0.001
Y + CL_PLAND + SDD + CL_PLAND^2 + SDD^2 + BF + JM + JAM + DFH	14	21	< 0.001
Y + CL_PLAND + BF + JM + JAM + DFH	14	18	< 0.001
Y + SDD + Lg SDD + (SDD × Lg SDD) + BF + JM + JAM + DFH	14	20	< 0.001

Table E-5 (cont'd)

Y + Lg SDD + BF + JM + JAM + DFH	14	18	< 0.001
Y + CL_PLAND + SDD + BF + JM + JAM + DFH	15	19	< 0.001
Y + SDD + Lg SDD + BF + JM + JAM + DFH	15	19	< 0.001
Y + CL_PLAND + Lg SDD + BF + JM + JAM + DFH	15	19	< 0.001
Y + CL_PLAND + SDD + (CL_PLAND × SDD) + BF + JM + JAM + DFH	15	20	< 0.001
Y + Lg SDD + Lg SDD^2 + BF + JM + JAM + DFH	16	19	< 0.001
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD) + BF + JM + JAM + DFH	16	22	< 0.001
Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2 + BF + JM + JAM + DFH	16	21	< 0.001
Y + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH	16	20	< 0.001
Y + CL_PLAND + SDD + Lg SDD + BF + JM + JAM + DFH	16	20	< 0.001
Y + SDD + Lg SDD + SDD^2 + Lg SDD^2 + BF + JM + JAM + DFH	17	21	< 0.001
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD) + BF + JM + JAM + DFH	17	22	< 0.001
Y + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2 + BF + JM + JAM + DFH	17	23	< 0.001
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + BF + JM + JAM + DFH	17	21	< 0.001
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH	17	21	< 0.001

Y [a]: Yr

CL_PLAND [b]: Proportion of cultivated land

Table E-5 (cont’d)

SDD [c]: Snow depth days (i.e., winter severity) from immediately preceding winter

CL_PLAND^2 [d]: Proportion of cultivated land ^{2}

SDD^2 [e]: Snow depth days ^{2}

FH [f]: Total fall harvest from the previous calendar year

Lg SDD [g]: Year lag of winter severity (i.e., snow depth days from 2 winters previous)

Lg CL_PLAND [h]: Proportion of cultivated land from 2 winters previous

Lg SDD^2 [i]: Snow depth days from 2 winters previous ^{2}

Lg CL_PLAND^2 [j]: Proportion of cultivated land from 2 winters previous ^{2}

BF [k]: Brood flock count from preceding August

JM [l]: Total juvenile males in current spring harvest

JAM [m]: Ratio of juvenile males to adult males in current spring harvest

DFH [n]: Drivers of fall harvest: May rainfall + Landscape-level contrast-weighted edge density + Landscape-level contrast-weighted edge density ^{2} + Interspersion and juxtaposition + Contrast-weighted edge density of evergreen forest + Mixed forest mean shape index + Median patch area of deciduous forest

Table E-6. Model set for analysis of drivers of spring abundance of wild turkeys the Adirondacks and Tug Hill of New York during 1985-2010. Models below are for fixed effects only. Each of the models included random intercepts for year and the error structure previously chosen by AIC. K is the number of parameters. w is the model weight.

Model name	ΔAIC	K	w
Y [a] + Lg SDD [b]	0	5	0.125
Y + SDD [c] + Lg SDD	1.6	6	0.051
Y + FH [d] + Lg SDD	2	6	0.046
Y + CL_PLAND [e] + Lg SDD	2	6	0.046
Y + Lg SDD + Lg SDD^2 [f]	2	6	0.046
Y + SDD + Lg SDD + (SDD × Lg SDD)	2.7	7	0.033
Y + FH	2.9	5	0.029
Y + SDD	2.9	5	0.029
Y + CL_PLAND [g]	2.9	5	0.029
Y + CL_PLAND + CL_PLAND^2	3.2	6	0.025
Y + SDD + SDD^2 [h]	3.6	6	0.021
Y + FH + SDD + Lg SDD	3.6	7	0.020
Y + CL_PLAND + SDD + Lg SDD	3.6	7	0.020
Y + Lg CL_PLAND [i] + Lg SDD + (Lg CL_PLAND × Lg SDD)	3.6	7	0.020
Y + FH + CL_PLAND + Lg SDD	4	7	0.017
Y + FH + Lg SDD + Lg SDD^2	4	7	0.017
Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2	4.3	8	0.014

Table E-6 (cont'd)

Y + SDD + Lg SDD + SDD^2 + Lg SDD^2	4.5	8	0.013
Y + FH + SDD + Lg SDD + (SDD × Lg SDD)	4.7	8	0.012
Y + Lg SDD + BF + JM + JAM + DFH	4.8	12	0.011
Y + FH + SDD	4.9	6	0.011
Y + FH + CL_PLAND	4.9	6	0.011
Y + CL_PLAND + SDD	4.9	6	0.011
Y + FH + CL_PLAND + CL_PLAND^2	5.2	7	0.009
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	5.3	8	0.009
Y + FH + SDD + SDD^2	5.5	7	0.008
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)	5.6	8	0.008
Y + FH + CL_PLAND + SDD + Lg SDD	5.6	8	0.008
Y + FH + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	5.6	8	0.008
Y + CL_PLAND + SDD + CL_PLAND^2 + SDD^2	6.1	8	0.006
Y + FH + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2	6.3	9	0.005
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	6.3	9	0.005
Y + SDD + Lg SDD + BF + JM + JAM + DFH	6.4	13	0.005
Y + CL_PLAND + Lg SDD + BF + JM + JAM + DFH	6.5	13	0.005
Y + FH + SDD + Lg SDD + SDD^2 + Lg SDD^2	6.5	9	0.005
Y + CL_PLAND + BF [j] + JM [k] + JAM [l] + DFH [m]	6.5	12	0.005

Table E-6 (cont'd)

Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)	6.7	9	0.004
Y + Lg SDD + Lg SDD^2 + BF + JM + JAM + DFH	6.7	13	0.004
Y + FH + CL_PLAND + SDD	6.9	7	0.004
Y + CL_PLAND + SDD + (CL_PLAND × SDD)	6.9	7	0.004
Y + SDD + BF + JM + JAM + DFH	6.9	12	0.004
Y + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2	7	10	0.004
Y + FH + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	7.3	9	0.003
Y + SDD + Lg SDD + (SDD × Lg SDD) + BF + JM + JAM + DFH	7.5	14	0.003
Y + FH + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)	7.6	9	0.003
Y + SDD + SDD^2 + BF + JM + JAM + DFH	7.8	13	0.003
Y + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH	7.9	14	0.002
Y + CL_PLAND + CL_PLAND^2 + BF + JM + JAM + DFH	7.9	13	0.002
Y + CL_PLAND + SDD + Lg SDD + BF + JM + JAM + DFH	8	14	0.002
Y + FH + CL_PLAND + SDD + CL_PLAND^2 + SDD^2	8	9	0.002
Y + FH + Lg CL_PLAND + Lg SDD + Lg $CL\_PLAND^{2\ n}$ + Lg SDD^2 + (Lg CL_PLAND × Lg SDD)	8.2	10	0.002
Y + FH + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	8.3	10	0.002
Y + CL_PLAND + SDD + BF + JM + JAM + DFH	8.5	13	0.002

Table E-6 (cont'd)

Y + FH + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)	8.6	10	0.002
Y + FH + CL_PLAND + SDD + (CL_PLAND × SDD)	8.9	8	0.001
Y + FH + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2	8.9	11	0.001
Y + SDD + Lg SDD + SDD^2 + Lg SDD^2 + BF + JM + JAM + DFH	9.3	15	0.001
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH	9.4	15	0.001
Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2 + BF + JM + JAM + DFH	9.8	15	< 0.001
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + BF + JM + JAM + DFH	10	15	< 0.001
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD) + BF + JM + JAM + DFH	10	16	< 0.001
Y + CL_PLAND + SDD + (CL_PLAND × SDD) + BF + JM + JAM + DFH	11	14	< 0.001
Y + CL_PLAND + SDD + CL_PLAND^2 + SDD^2 + BF + JM + JAM + DFH	11	15	< 0.001
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD) + BF + JM + JAM + DFH	11	16	< 0.001
Y + FH + Lg CL_PLAND + SDD + Lg SDD + Lg CL_PLAND^2 + SDD^2 + Lg SDD^2 + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	12	13	< 0.001
Y + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2 + BF + JM + JAM + DFH	12	17	< 0.001
Y + FH + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2 + (CL_PLAND × SDD) + (SDD × Lg SDD)	12	13	< 0.001

Y [a]: Yr

Lg SDD [b]: Year lag of winter severity (i.e., snow depth days from 2 winters previous)

Table E-6 (cont'd)

SDD [c]: Snow depth days (i.e., winter severity) from immediately preceding winter

FH [d]: Total fall harvest from the previous calendar year

CL_PLAND [e]: Proportion of cultivated land

Lg SDD^2 [f]: Snow depth days from 2 winters previous ^{2}

CL_PLAND^2 [g]: Proportion of cultivated land ^{2}

SDD^2 [h]: Snow depth days ^{2}

Lg CL_PLAND [i]: Proportion of cultivated land from 2 winters previous

BF [j]: Brood flock count from preceding August

JM [k]: Total juvenile males in current spring harvest

JAM [l]: Ratio of juvenile males to adult males in current spring harvest

DFH [m]: Drivers of fall harvest: June rainfall + Landscape-level contrast-weighted edge density + Interspersion and juxtaposition + (June rainfall × Interspersion and juxtaposition)

Lg CL_PLAND^2 [n]: Proportion of cultivated land from 2 winters previous ^{2}

Table E-7. Model set for analysis of drivers of spring abundance of wild turkeys the St. Lawrence Plain and Champlain Valley of New York during 1985-2010. Models below are for fixed effects only. Each of the models included all the random effects and the error structure previously chosen by AIC. K is the number of parameters. w is the model weight.

Model name	ΔAIC	K	w
Y [a] + CL_PLAND [b]	0	7	0.091
Y + CL_PLAND + Lg SDD [c]	0.6	8	0.066
Y + CL_PLAND + SDD [d]	1.1	8	0.053
Y + CL_PLAND + SDD + Lg SDD	1.2	9	0.051
Y + FH [e] + CL_PLAND	2	8	0.034
Y + CL_PLAND + CL_PLAND^2 [f]	2	8	0.034
Y + CL_PLAND + SDD + (CL_PLAND × SDD)	2.3	9	0.029
Y + Lg CL_PLAND [g] + Lg SDD + (Lg CL_PLAND × Lg SDD)	2.4	9	0.027
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)	2.6	10	0.024
Y + FH + CL_PLAND + Lg SDD	2.6	9	0.024
Y + FH + CL_PLAND + SDD	3	9	0.020
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	3.1	10	0.019
Y + FH + CL_PLAND + SDD + Lg SDD	3.2	10	0.019
Y + Lg SDD	3.9	7	0.013
Y + FH + CL_PLAND + CL_PLAND^2	4	9	0.013
Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2 [h]	4.1	10	0.012
Y + FH + CL_PLAND + SDD + (CL_PLAND × SDD)	4.3	10	0.011

Table E-7 (cont'd)

Y + FH + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	4.4	10	0.010
Y + SDD + Lg SDD	4.5	8	0.010
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)	4.5	11	0.010
Y + CL_PLAND + SDD + CL_PLAND^2 + SDD^2 [i]	4.6	10	0.009
Y + SDD	4.6	7	0.009
Y + FH + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD)	4.6	11	0.009
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	5	11	0.007
Y + FH + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD)	5.1	11	0.007
Y + Lg SDD + Lg SDD^2	5.4	8	0.006
Y + FH	5.5	7	0.006
Y + FH + Lg SDD	5.9	8	0.005
Y + FH + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2	6.1	11	0.004
Y + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2	6.1	12	0.004
Y + SDD + SDD^2	6.2	8	0.004
Y + SDD + Lg SDD + (SDD × Lg SDD)	6.5	9	0.004
Y + FH + SDD + Lg SDD	6.5	9	0.004
Y + FH + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD)	6.5	12	0.004
Y + FH + CL_PLAND + SDD + CL_PLAND^2 + SDD^2	6.6	11	0.003

Table E-7 (cont'd)

Y + FH + SDD	6.6	8	0.003
Y + FH + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	7	12	0.003
Y + FH + Lg SDD + Lg SDD^2	7.3	9	0.002
Y + SDD + Lg SDD + SDD^2 + Lg SDD^2	7.5	10	0.002
Y + FH + Lg CL_PLAND + Lg SDD + Lg CL_$PLAND^2$ [j] + Lg SDD^2 + (Lg CL_PLAND × Lg SDD)	8	12	0.002
Y + FH + CL_PLAND + SDD + Lg SDD + CL_$PLAND^2$ + SDD^2 + Lg SDD^2	8.1	13	0.002
Y + FH + SDD + SDD^2	8.2	9	0.002
Y + FH + SDD + Lg SDD + (SDD × Lg SDD)	8.5	10	0.001
Y + FH + SDD + Lg SDD + SDD^2 + Lg SDD^2	9.5	11	< 0.001
Y + FH + CL_PLAND + SDD + Lg SDD + CL_$PLAND^2$ + SDD^2 + Lg SDD^2 + (CL_PLAND × SDD) + (SDD × Lg SDD)	11	15	< 0.001
Y + FH + Lg CL_PLAND + SDD + Lg SDD + Lg CL_$PLAND^2$ + SDD^2 + Lg SDD^2 + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD)	12	15	< 0.001
Y + CL_PLAND + BF [k] + JM [l] + JAM [m] + DFH [n]	12	14	< 0.001
Y + CL_PLAND + Lg SDD + BF + JM + JAM + DFH	13	15	< 0.001
Y + CL_PLAND + SDD + BF + JM + JAM + DFH	14	15	< 0.001
Y + CL_PLAND + SDD + Lg SDD + BF + JM + JAM + DFH	14	16	< 0.001
Y + CL_PLAND + CL_$PLAND^2$ + BF + JM + JAM + DFH	14	15	< 0.001
Y + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH	15	16	< 0.001

Table E-7 (cont'd)

Y + CL_PLAND + SDD + (CL_PLAND × SDD) + BF + JM + JAM + DFH	15	16	< 0.001
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + BF + JM + JAM + DFH	15	17	< 0.001
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + BF + JM + JAM + DFH	16	17	< 0.001
Y + Lg SDD + BF + JM + JAM + DFH	16	14	< 0.001
Y + SDD + Lg SDD + BF + JM + JAM + DFH	17	15	< 0.001
Y + CL_PLAND + Lg SDD + CL_PLAND^2 + Lg SDD^2 + BF + JM + JAM + DFH	17	17	< 0.001
Y + SDD + BF + JM + JAM + DFH	17	14	< 0.001
Y + CL_PLAND + SDD + Lg SDD + (CL_PLAND × SDD) + (SDD × Lg SDD) + BF + JM + JAM + DFH	17	18	< 0.001
Y + CL_PLAND + SDD + CL_PLAND^2 + SDD^2 + BF + JM + JAM + DFH	17	17	< 0.001
Y + Lg SDD + Lg SDD^2 + BF + JM + JAM + DFH	17	15	< 0.001
Y + SDD + Lg CL_PLAND + Lg SDD + (Lg CL_PLAND × Lg SDD) + (SDD × Lg SDD) + BF + JM + JAM + DFH	17	18	< 0.001
Y + SDD + SDD^2 + BF + JM + JAM + DFH	18	15	< 0.001
Y + SDD + Lg SDD + (SDD × Lg SDD) + BF + JM + JAM + DFH	19	16	< 0.001
Y + CL_PLAND + SDD + Lg SDD + CL_PLAND^2 + SDD^2 + Lg SDD^2 + BF + JM + JAM + DFH	19	19	< 0.001
Y + SDD + Lg SDD + SDD^2 + Lg SDD^2 + BF + JM + JAM + DFH	20	17	< 0.001

Y [a]: Yr

CL_PLAND [b]: Proportion of cultivated land

Table E-7 (cont'd)

Lg SDD [c]: Year lag of winter severity (i.e., snow depth days from 2 winters previous)

SDD [d]: Snow depth days (i.e., winter severity) from immediately preceding winter

FH [e]: Total fall harvest from the previous calendar year

CL_PLAND^2 [f]: Proportion of cultivated land ^{2}

Lg CL_PLAND [g]: Proportion of cultivated land from 2 winters previous

Lg SDD^2 [h]: Snow depth days from 2 winters previous ^{2}

SDD^2 [i]: Snow depth days ^{2}

Lg CL_PLAND^2 [j]: Proportion of cultivated land from 2 winters previous ^{2}

BF [k]: Brood flock count from preceding August

JM [l]: Total juvenile males in current spring harvest

JAM [m]: Ratio of juvenile males to adult males in current spring harvest

DFH [n]: Drivers of fall harvest: Proportion of grassland + Proportion of grassland ^{2} + Proportion of mixed forest + Proportion of mixed forest ^{2}

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