AN INTEGRATIVE APPROACH TO CONSERVATION OF THE CRESTED CARACARA (*CARACARA CHERIWAY*) IN FLORIDA: LINKING DEMOGRAPHIC AND HABITAT MODELING FOR PRIORITIZATION

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ABSTRACT

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The Crested Caracara (*Caracara cheriway*) occurs in Florida as an isolated population in the south-central region. Caracaras currently occur almost exclusively on ranchlands, most of which are privately owned. The status of Florida's Caracara population has been a subject of concern as conversion of grasslands and pasture to residential and commercial development has accelerated, particularly within the past 10 years. Our objectives for this work were to provide a better understanding of the specific ecological needs of the Caracara with regard to habitat and to use known demographic information to develop a population model suitable for assessment of extinction risk.

To achieve this, we used population viability analyses and a GIS. Using all available data, we constructed a population viability model to determine the most important demographic parameters and assess viability. The most important demographic variable impacting viability was adult survival, and our demographic model indicated that this population is stable under current conditions. However, current conditions are unlikely to persist and multiple habitat loss scenarios were explored. Results indicate abrupt habitat loss increases risk compared to gradual loss of the same magnitude. Using GIS, we evaluated habitat composition of known caracara home ranges and used the Mahalanobis distance statistic to build a predictive habitat model. Geographic layers used were recoded to reflect the landscape context surrounding each cell within an average home range. Models were tested using an independent data set. Results indicated that heterogeneity is critical and we identified seven landscape characteristics, including five vegetation types and both lentic and lotic water, necessary in maintaining suitable habitat in Florida. Our final habitat model performed well in both predictive accuracy and in reducing the portion of the study area judged suitable. Finally, we used occurrence data to identify distribution patterns of habitat use. A core area of habitat use was readily identified, and habitat use decreased consistently across buffers extending out from the core. This was integrated with our demographic and habitat models to prioritize habitat for conservation, and construct models simulating habitat loss in particular regions in Florida and their associated risk of population decline.

I dedicate this
to my grandmother, Bonnie C. Swain (1934-2006),
for showing me the kind of woman that I wanted to be,
and to my husband, Rolland S. Barnes,
who has supported me along every step of this journey.

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CHAPTER I

GENERAL INTRODUCTION

As the human population continues to increase, natural habitat is disappearing at an alarming rate. This loss of habitat and the resulting fragmentation are two of the most serious threats to many species today (Hoekstra et al. 2005; Soule 1986; Wiegand et al. 1999). Often, species are seriously imperiled before researchers are aware that there is a threat. Due to the current rate of loss of biodiversity, conservation biologists are often faced with the problem of making management recommendations with little data (Pullin & Knight 2001). This lack of information is exacerbated by the decreased value currently placed on natural history and basic ecological studies (Futuyma 1998; O'Connor 2002).

These factors culminate in the need for tools that will allow us to focus limited resources by prioritizing research needs and assessing management recommendations to maximize our conservation efforts. Two of the most powerful tools currently available to do this are population viability analyses (PVA) and geographic information systems (GIS) analyses (Reed et al. 2002).

Population Viability Analysis

Population viability analysis (PVA) is an approach and a process that utilizes evaluation of data and models to determine the probability of persistence for a population for a given period of time (Akçakaya & Sjogren-gulve 2000; Boyce 1992). While it is often linked specifically to the idea of finding a minimum viable population (MVP) number (Gilpin & Soule 1986), the use of PVA is not limited to this type of analysis, and problems with seeking an absolute number or absolute rates of extinction are reviewed thoroughly in the literature (Beissinger & Westphal 1998; Brook et al. 2000; Coulson et al. 2001). Population models can be spatially simple, assuming homogenous, contiguous landscapes, or they can be more complex, as in spatially-explicit metapopulation models. Models can be individual, stage, population, or multiple-species based. They can also be deterministic or can incorporate stochasticity. PVA can be used at a multitude of complexity levels, making it a powerful and flexible tool that can be used to address a variety of questions (Burgman 2000). Of particular importance to conservation biologists, PVA can be used to determine the relative risk of extinction, despite uncertainty in parameters, and to explore the potential impacts of various changes such as habitat loss or management plans (Akçakaya & Raphael 1998; McCarthy et al. 2003). In addition, it can be used to generate testable hypotheses that can then be evaluated with sound ecological studies.

Habitat models using GIS can be paired with population models to make powerful spatially-explicit models that can then make predictions over time and space (Akçakaya et al. 1995; Root 1998; Wiegand et al. 2005). This allows recommendations to be made over multiple spatial scales, assessing each patch or region based on its contribution to the conservation of the focal species.

Predictive Habitat Modeling

With the advent of GIS, spatial analysis can now be done using large amounts of data across scales that previously would have been nearly impossible. This allows for a quantitative characterization of species' habitat using specific geographic attributes such as vegetation, cover, and hydrology. This can then be used to address questions and make predictions concerning habitat requirements, suitability, and occurrence of a species or population (Kautz & Cox 2001;

Tucker et al. 1997), much more accurately than simply relying on expert opinion (Corsi et al. 2000; Guisan & Zimmermann 2000). In addition, it can be used to incorporate logistic information such as land use and ownership, or development pressure to assess how much of a species range is currently protected in reserves or public lands and determine what is required for further protection (Jennings 2000; Kiester et al. 1996).

Characterization of the specific ecological requirements for species habitat is critical for conservation efforts (Brambilla et al. 2006; Clark et al.1993; Gibson et al. 2004). For species that are well studied, these requirements may be described, although these are often focused only within the confines of the study area, rarely the entire species' range. For species that are of conservation concern but are not well-studied, the only data available may be as sparse as a list of localities in which individuals have been sighted. In either of these cases, predictive modeling can be a useful technique. Predictive Modeling (PM) relies on either deductive methods, where ecological variables thought to be important for a species are used to identify habitat, or inductive methods, where significant correlations between ecological variables and presence of individuals is used to identify habitat (Guisan & Zimmermann 2000). By whichever method, these ecological variables are then used to look at larger spatial scales (often an entire species or population range, or political extent) and predict additional areas that are likely to provide suitable habitat based on their ecological similarity.

Quantifying habitat is often not enough, however. Prioritizing areas for conservation is an important next step in managing species at risk. All habitat can rarely be conserved and/or managed for a population, so we must determine which areas should be the focus of conservation efforts. Ideally, we would assess and use habitat quality as a metric for prioritization. However, habitat quality should be tied to fitness, and we have this level of data for only the most well-studied species (e.g. Davenport et al. 2000; Root 1998). For metapopulations, we could prioritize habitat based on source-sink dynamics, or if these data are lacking, follow a simple 'bigger patches are better' approach. For multiple species, prioritization is often based on count data where the highest number of different species occurs, e.g., determination of biodiversity hotspots (Kiester et al. 1996; Moilanen et al. 2005). No matter which method is used, prioritizing habitat is an important step for effective management of populations and species at risk.

Crested Caracara in Florida

These assessment tools are particularly useful for areas of high biodiversity experiencing high rates of habitat loss, such as the state of Florida. Florida currently has 100 species federally listed as endangered or threatened (U.S. Fish & Wildlife 2004). The human population of South Florida alone is projected to increase 56% between 2000 and 2030, making habitat loss and conversion the greatest threats for this region (BEBR 2001). This is of special concern for species occurring primarily on private, unmanaged lands, such as the Crested Caracara (*Caracara cheriway*).

The Crested Caracara occurs in Florida as an isolated population in the south-central region. This population is disjunct from the larger species range, which extends from extreme southern Texas and Arizona through Mexico and into northern South America (Morrison 1996). The Caracara population in Florida is currently listed as threatened at the state and federal level. The Caracara is a large, opportunistic raptor, feeding both on carrion and live prey (Morrison 1996; Travaini et al. 2001). Caracaras are able to achieve high flight speeds, but spend most of their foraging time on the ground, and can be observed running after prey (Layne 1996). Long-lived and monogamous, Caracaras are non-migratory, territorial and seem to prefer open grassland (Morrison 1996). Most of the state's dry prairies have been converted to livestock pastures or farmland, and more than 80% of known nest locations occur on privately owned land (Morrison & Humphrey 2001). Data on basic life history parameters exist for this species from long-term banding studies conducted over the past decade, which can be used to build a basic model (Morrison 1999, 1998, 2003; Nemeth & Morrison 2002). However, there are still many gaps in our knowledge of the species that are of critical importance to their conservation that can be addressed using PVA and GIS analyses.

Adults maintain territories year-round (Morrison 1996). Breeding takes place between September and April, and double-brooding has been observed (Dickinson & Arnold 1996; Morrison 1998). Breeding is thought to occur at around 3-4 years of age (Nemeth & Morrison 2002). Juveniles leave the natal territory before the next clutch is laid, and have been observed to aggregate in large flocks of 30 or more individuals, but this life history stage has garnered little research interest (Morrison 1996). While some demographic parameters have been relatively well studied, such as nest productivity and age-specific survival, uncertainty in basic parameters such as longevity and dispersal dynamics still exist (Morrison 1999, 2003)

Previous estimates placed the statewide population between 400 and 500 individuals (Layne 1996). However, current research suggests that this was much too low and a more reasonable estimate is 1000 individuals (Morrison, pers. comm.). Gaining an accurate account of population size has proven difficult, and even impossible due to the proportion that occurs on private lands (Morrison & Humphrey 2001). This makes monitoring population changes problematic, as well. As a result, population status is difficult to ascertain, though the population is currently thought to be on a long-term decline (Millsap et al. 1990; Layne 1996). The state recovery plan for the Caracara specifically identifies development of a population viability analysis as a high priority, in order to determine population status, and also to determine which ecological factors have the greatest impact on survival (U.S. Fish & Wildlife 1999). PVA is an ideal tool for the Caracara, as we can use it to assess aspects of population dynamics that cannot be gained through direct fieldwork or observation, as many habitat patches are inaccessible to researchers.

Caracaras are associated with open grasslands; in Florida this is the dry prairie ecosystem (Abrahamson & Hartnett 1990; del Hoyo et al. 1994; Evans 1982). In Florida, dry prairies are characterized by being treeless or nearly so, and ground vegetation consists mostly of a variety of grass species. Water tables remain below ground for most of the year. Fire is an important factor in the dynamics of this system, and anthropogenic suppression of fire is the most common cause of successional changes. Current trends predict that the majority of future habitat loss and conversion in Florida will be in dry prairie and flatwood ecosystems (Abrahamson & Hartnett 1990). Caracaras presumably require open areas to hunt, and occasional trees for nesting, but little else is known about the specific habitat features that they require (Morrison & Humphrey 2001; U.S. Fish & Wildlife 1999). Conversion of dry prairie to ranching and agriculture as well as development is accelerating (Morrison & Humphrey 2001), and suppression of fire may allow successional changes. Habitat loss and conversion seem to be the largest threats to the Caracara (U.S. Fish & Wildlife 1999). My research will lead to a better understanding of the specific ecological needs of the Caracara with regard to habitat, which is a high priority for their recovery.

Areas currently being managed for native plant and animal species in Florida do not seem to be attractive to Caracaras, as they have been found there only rarely. This may indicate that there is high variability among grassland species as to specific habitat features, making a general management plan for this ecosystem ineffective (Morrison & Humphrey 2001). The frequent occurrence of Caracaras on private pastureland may indicate that there are particular habitat features present that are missing or reduced on publicly managed lands. Understanding habitat preference will be imperative for both restoration efforts, as well as management of current habitat.

Goals of this Research

This body of work is meant to demonstrate a holistic approach to conservation of the Crested Caracara in Florida. We use all available data to develop a population viability model, which we then use to address specific questions regarding viability under various scenarios, as well as to test the relative impact of assumptions used in our model. In addition, we use this species as a case study to determine if a more complex model gives us more insight into population risk than a more parsimonious approach.

We also present a modeling framework that uses the most commonly available data, presence of individuals, to build a predictive habitat model utilizing GIS and the Mahalanobis Distance Statistic, and then demonstrate a strategy for using available occurrence data to prioritize those areas identified as suitable habitat across the landscape for the population of Crested Caracaras in Florida. After prioritizing habitat, we then link this demographic model to our new map showing the habitat prioritization scheme, and used it to identify the differential impact of habitat loss in various regions on risk of population decline.

In addition to the obvious emphasis of this research to positively impact the conservation of the Caracara in Florida, we also use methods that can be applied to other species. More specifically, we show in our population modeling approach how to test the efficacy of parsimony vs. complexity in stage matrix construction. In our predictive modeling approach, we show how the context of the surrounding area can be incorporated into model construction. And in our approach to prioritize habitat for the population, we show how occurrence data can be used for those populations that exhibit clustering in their distribution across the landscape.

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CHAPTER II

EVALUATING ASSUMPTIONS AND PARSIMONY: A POPULATION VIABILITY MODEL FOR THE CRESTED CARACARA IN FLORIDA

INTRODUCTION

Population viability analysis (PVA) is an approach and a process, allowing evaluation of data and models to determine the probability of persistence for a population for a given period of time (Akçakaya & Sjogren-gulve 2000; Boyce 1992). When PVA was originally proposed by Gilpen & Soule (1986), it was specifically designed to estimate a minimum viable population (MVP) number. Criticisms have been waged against the use of PVA as a method of estimating absolute rates of extinction or estimation of an MVP ever since (e.g., Beissinger & Westphal 1998; Brook et al. 2000; Coulson et al. 2001; Ludwig 1999). However, the use of PVA is not limited to this type of analysis. As PVA has become more frequently used and evaluated, its utility and power are no longer linked to absolute predictions, but rather to assessing relative impacts of various scenarios, testing the impact of uncertainty of parameters, evaluating potential impacts of habitat loss, and producing testable hypotheses (Ball et al. 2003; Boyce 1992; McCarthy et al. 2003; Reed et al. 2002). These can then be used to gain insight into population dynamics and ecological interactions, guide decision making for management, as well as guide conservation research efforts.

Aside from criticisms of the use of PVA for absolute predictions, concerns have also been raised regarding the models embedded in the PVA process: more specifically the model structure (Beissinger & Westphal 1998), density dependence used (Mills et al. 1996; Sabo et al. 2004), time line of the model (Fieberg & Ellner 2001; McCarthy et al. 2003), and differences in parameter estimation (White et al. 2002). In contrast, Açkacaya & Sjogren-gulve (2000), Brook et al. (2002) and Burgman (2000) support the use of PVA in lieu of alternatives such as using subjective expert opinion even when there are uncertainties in parameter estimates, as long as assumptions used in the model are made explicit. Sabo (2004) states that PVA can be useful for relative assessments, even when an underlying assumption in the PVA such as density dependence is inaccurate. Few rules exist for construction of PVA, although there is an often cited rule of thumb of 'simple is better' (Morris & Doak 2002), meaning that fewer assumptions and a more parsimonious modeling approach are best. However, PVA can be used at a variety of complexity levels appropriate for the level of data available and the questions of interest, making it a powerful and flexible tool that can be used to address a multitude of questions (Burgman 2000). These types of models have been built for a variety of taxa, including mammals (e.g. Brito & Grelle; Haines et al. 2006; Kohlmann et al. 2005), birds (e.g. Johnson & Braun 1999; Root 1998; Walters et al. 2002), herps (Paul 2004; Pellet et al. 2006), fishes (e.g. Legault 2005; Root 2002), invertebrates (e.g. Bergman & Kindvall 2004; Schtickzelle et al. 2005), and plants (e.g. Nantel et al. 1996; Obioh & Isichei 2007) incorporating varying levels of sophistication.

We developed a PVA for the Crested Caracara (*Caracara cheriway*) in Florida, a population both state and federally listed as threatened. The Crested Caracara occurs in Florida as an isolated population in the south-central region. This population is disjunct from the larger species range, which extends from the southern United States through Mexico and into northern South America (Morrison 1996). Long-lived and monogamous, Caracaras are non-migratory, territorial and were formerly documented as inhabiting native prairie in this region (Nicholson 1929; Howell 1932), but historic population numbers and the extent of historic nesting activity throughout the state are not known.

Conversion of dry prairie has occurred throughout much of the Caracara's range, first to ranching and agriculture and, more recently, to urban development. Particularly in the last 10 years, land use patterns have changed dramatically throughout south-central Florida as land prices have escalated. Current estimates place more than 80% of known nests on privately owned land (Morrison & Humphrey 2001). Since the mid-1990s, progress has been made toward understanding the life history and determining the status of the Caracara in Florida, particularly its current distribution and reproductive biology (Morrison 1998, 1999, 2003; Nemeth and Morrison 2002). However, there are still many gaps in our knowledge of the species that are of critical importance to their conservation that can be addressed using PVA.

Previous estimates place statewide population between 400 and 500 individuals (Layne 1996). More recently, this estimate has been increased to a conservative estimate of 1000 individuals, citing that earlier estimates were too low (J. Morrison, pers. comm.). However, accurately estimating population size has proved difficult due to the proportion of the population that occurs on private lands (Morrison & Humphrey 2001). This makes monitoring population changes problematic, as well. As a result, population status is difficult to ascertain, although the population is currently thought to be stable after a long-term decline (Evans 1982; Morrison, 1996). PVA is an ideal tool for the Caracara, as we can use it to assess aspects of population dynamics that can be difficult to gain through direct fieldwork or observation, as many habitat patches are inaccessible to researchers due to their occurrence on private lands. In addition, the PVA allows us to address these aspects in a timely manner, which is particularly important for this species that primarily occurs on privately owned lands that are subject to changes in the economy of one particular land use: cattle ranching.

Our goals for this research were two-fold. Primarily, we addressed specific questions regarding the current status of the Crested Caracara in Florida based on available demographic data, and the relative risk under different scenarios. We used this model to fill specific gaps in our understanding of the population dynamics of this population and guide future research and management. These gaps include assessing this population's ability to respond to perturbations, identifying which parameters have the greatest influence on growth rate and risk of population decline, and assessing how loss of habitat impacts population persistence. Secondly, we directly assessed the impacts of different assumptions on the model output, to address the concerns and criticisms leveled at PVA. We looked at the impact of density dependence, uncertainty in each parameter using sensitivity analysis, and identify the parameter of greatest influence using elasticity analysis. We also evaluate multiple models with different stage matrix structures, incorporating varying levels of life history complexity. This increased the number of assumptions that we made, as all models were constructed using the same underlying data. However, we wanted to determine if varying levels of complexity substantially changed model outcomes, and if this allowed us to gain insight into potential dynamics at work within the Caracara population compared to a more parsimonious model.

METHODS

Building the Population Viability Analysis

Developing the Stage Matrix.—We used all available demographic data (Morrison 1996, 1998, 1999, 2003; Nemeth & Morrison 2002) to guide the structure of the stage matrix used in the population viability analysis (Table 1). We constructed three separate stage matrices, with three, four, or five life stages, respectively, to incorporate increasing levels of demographic complexity. All models are females-only, and fecundity is defined as the annual number of daughters hatched per female. All stage matrices were constructed using this same pool of data. The structure and assumptions of each are described below. We describe the data used to construct our simple 3-stage model, and then describe how these data were modified and used to construct more complex models with additional life stages.

3 –Stage Model- We determined that a 3-stage matrix was most appropriate for our simple model based on our understanding of the distinct behavioral stages for this species: first year (hatching to 1 year of age), juvenile (>1 to 3 years of age), and adult (3+ years of age) Yearlings can remain on the natal territory for much of the first year, often remaining until the adults renest (Morrison 1996, 1998). For this life stage, they are not sexually mature and show juvenile plumage (Morrison 2002). Juveniles are largely nomadic and gregarious, congregating in large, often mixed species groups and roam the landscape (Morrison 1996). After becoming sexually mature, which has been documented in birds as young as 3 years of age (Morrison 1999), adults settle on a nesting territory, if territory is available. They become territorial, exhibit high site fidelity, and are intolerant of conspecifics (Morrison 1996). Field data have largely been collected and categorized based on these distinct life stages.

The Caracara is sexually mature at 3-4 years of age (Layne 1996; Nemeth & Morrison 2002). In calculating fecundity for the adult stage (3+ years), 97-100% of pairs attempt breeding (Morrison 1999) but the adult stage may include some adult individuals that are not paired; to account for this we decreased the percent of females breeding to 90% of the estimated number of females. A small percentage of paired females double brood (21.7%, Morrison 1999), although this estimate is thought to be high and is more conservatively estimated at 10-15%. Average clutch size for a single brood is 2.3 eggs (Morrison 1999) (assuming a 1:1 sex ratio, this equals 1.15 ♀), average clutch size for the first of two broods is 2.5, and for the second of two broods is 1.86 (Morrison 1998). Using a starting point of 90% of females breeding, we estimated that 15% of those double brooded. Overall hatching success has been reported as 75% for Caracaras in Texas (Dickinson & Arnold 1996) and in Florida (Morrison 1996), but data from 98 known size clutches showed a hatching success of 90% for first broods, and 64% for second broods (Morrison 1999). Based on these data, adult stage fecundity was calculated as 1.02. We calculated a fecundity value of 0.031 for the juvenile stage, assuming that some precocious females are able to pair at the end of this stage, that they are only able to single brood, and that they have a 90% hatching success rate. Notice that we make no assumption that a precocious breeder in this stage has lower clutch size or hatching success than that of a breeder in the adult stage.

Annual survival for the Caracara in Florida has been reported as 0.906 for adult nesting females, and 0.694 for juveniles based on analyses using the program MARK (Morrison 2003), and we used these values to build our model. Survival for the juvenile stage was calculated based on a monthly survival rate of 0.97. Survival for the yearling stage incorporated the increased mortality experienced from hatching to independence, which occurs at approximately 4 months (Morrison 1999). Mean annual survival for the yearling stage was calculated as 0.44; annual survival for the juvenile stage was 0.694; and for the adult stage was 0.885 (assuming that 10% were non-breeding and still subject to the same level of mortality as juveniles, and 90% were nesting and subject to the 0.906 estimate for nesting adults). The stage matrix for our baseline 3-stage demographic model is shown in Table 3 and Fig. 1.

4-Stage Model- The 4-stage model is similar to the 3-stage, with one main exception. In this model, inexperienced breeding adults (ages 3-5) are separated into their own stage from experienced breeding adults (aged more than 5 years). A common pattern in bird species is increased fecundity with experience (Angelier & Dano 2006; Forslund & Part 1995), and in long-lived species annual survival often increases with age. While the data we are drawing from are too general to give specific estimates for this, incorporating this assumption may increase the realism of the model and allow us to test the impact of this assumption on risk. For this model we allowed survival and fecundity to increase from an inexperienced adult breeder stage to an experienced adult breeder stage The fecundity increase was demonstrated with an increase in the proportion of females that breed and double brood, and an increase in hatching success (Table 2). The stage matrix for our baseline 4 stage demographic model is shown in Table 4 and Fig. 2.

5-Stage Model- This model is similar to the previously described 4-stage model, however, we add one more stage to separate first year juveniles from second year juveniles. Survival studies supports that survival increases from first to second year juveniles (Morrison 2003). This allowed us to increase survival from one stage to the next, and also to associate the potential for precocious breeding with the second year juveniles (age 2-3) rather than with the entire juvenile stage (ages 1-3) used in the previous two models. The stage matrix for our baseline 5-stage demographic model is shown in Table 5 and Fig. 3.

Assumptions in all baseline models- Using these data, we developed a baseline model using the software program RAMAS GIS (Açkakaya & Root 2002). We built a female-only model, as fecundity for this species is most closely linked to females. To build this model we made a number of assumptions. First, we assumed that the sex ratio is 1:1, as we do not have data to support otherwise and this matches observations (J. Morrison, pers. comm.). Second, we built the model as a single population. The potential habitat model developed for this population (Chapter III) and the high vagility of this species (Morrison 1996) both indicate that the Caracara exists as one population in Florida. Third, we assumed that the population is currently near carrying capacity (K) and experiences ceiling density dependence. Finally, we ran the baseline model with the assumption that habitat is homogenous and does not change over time and that there are no catastrophes or other disasters affecting the population. Models were run for a timeframe of 50 years for 1000 replications. These models were stochastic, and we used a coefficient of variation (CV) of 0.10 for all parameters to represent year to year variation in the mean survival and fecundity values.

Analyses

Baseline Models- We ran baseline models for each of the three stage matrices to determine current risk of population decline under existing conditions, assuming current conditions persist for the duration of the model. For this and all additional scenarios, we report two types of results: a trajectory summary which shows the mean abundance of females over time, and interval percent decline, which shows the probability of a percent decline below initial abundance at any interval in the model duration.

Elasticity Analysis- Elasticity analysis is a measure of the contribution of each parameter within the stage matrix on the dominant eigenvalue (λ); the contribution of each parameter is reported as a proportion of 1 (Akçakaya & Root). We used elasticity analysis to determine which demographic parameter had the greatest impact on the model, relative to all other demographic parameters used. This was done for the 3-, 4-, and 5 stage models.

Sensitivity Analyses- Based on more recent estimates of population size in Florida, we used 1000 individuals (500 females) for the carrying capacity (K), and 800 individuals (400 females) for the initial abundance (J. Morrison, pers. comm.). To determine which parameter had the greatest impact on the stage matrix, we ran individual models with each parameter reduced by 10% in each of the three models. This allowed us to determine which stage had the greatest influence on population persistence, which can then be used to prioritize research and/or conservation efforts. This also allowed us to determine which parameters were most sensitive to uncertainty. We then compared these results across the three models to determine if the influence of specific parameters changed across the three models.

Habitat Loss Scenario - To simulate habitat loss and determine its impact on population risk, we ran scenarios reducing K to reflect changes in the amount of habitat available. We constructed a relatively realistic scenario showing gradual habitat loss over time. We ran two scenarios: the first showing a conservative loss of 10% of currently available habitat every ten years, and the second showing a more substantial loss of 20% every ten years; these scenarios were run for each of the three model types.

Perturbation Scenario- To determine the ability of this population to recover from a perturbation in carrying capacity, we reduced K at 10 years by 10% and 20% in two different scenarios. K was restored the following year. This allows us to measure population resilience, by determining how quickly the population could recover from a loss in K resulting from either habitat loss or some other catastrophe. We used this same perturbation scenario for all three models to see if the response would differ.

Density Dependence- In all baseline models, analyses, and scenarios described previously, ceiling density dependence was used. However, we also ran additional models to compare the impact on risk under exponential, contest (Beverton-Holt), and scramble (Ricker) density dependence types.

RESULTS

Baseline Models - The 3-stage baseline demographic model run using the stage matrix shown in Table 3 resulted in a finite rate of increase (λ) for this population of 1.0548. The extended 4- and 5-stage models resulted in λ =1.0611 and λ =1.0657, respectively (Tables 4 & 5). Abundance of females over time was similar among these three models, which is not surprising, as the growth rate indicates that this population could rapidly expand to K and this was the same in all three models (Figure 4). Risk of decline for the extended models differed slightly from the 3-stage model, however significant differences were in the lowest estimates of decline (Kolmogorov-Smirnov test statistic D; 4-stage: X= 0.0, $P<0.001$; 5-stage: X= 0.0, $P>0.001$) and were similar at higher rates of decline (Figure 5). This indicates that Florida's Caracara population is relatively stable with a zero probability of extinction (100% decline) over the next 50 years under current conditions, meaning no reduction or changes in habitat and no catastrophes. Because there was no substantial difference between these three different stage matrix models under all scenarios, we report the scenarios below based on the 3-stage model.

Elasticity Analysis- Elasticity analysis showed that the final stage survival parameter of each model had the greatest contribution to the dominant eigenvalue (λ) for that model; meaning that this parameter had the greatest influence on the finite growth rate. In the 3-stage baseline model, the adult stage survival parameter had an elasticity value of 0.575; for the 4-stage the experienced adult breeder survival parameter had a value of 0.421; for the 5-stage model, the experienced adult breeder survival parameter had a value of 0.404.

Sensitivity Analysis - Sensitivity analysis showed that the final stage (adults in the 3-stage model, experienced breeders in the 4- and 5-stage models) survival had the greatest effect on risk in all three models. Changes in yearling survival, juvenile survival, and adult (either experienced or inexperienced) fecundity all had roughly equivalent impacts on the population growth rate, and changes in juvenile fecundity had little effect on any of the models. In addition to assessing the relative contribution of parameters in the stage matrix, we also ran sensitivities on parameters such as changes in K and initial abundance values to determine their relative impact on abundance and risk. For all three models, we found that final stage survival had a significantly greater effect on risk over the baseline model than any other parameters, followed by a reduction in K (Figures 6-16). Although all three models showed that breeders have the greatest impact on persistence, only the 3-stage model shows a substantial decrease in abundance over time when the adult stage is lowered by 10% (Figure 6).

Habitat Loss Scenario –Reducing habitat by 10% every 10 years resulted in a substantial increase in population decline. Final female abundances decreased by >35% from baseline models (Figure 12). The probability of a 25% population decline increased from <1% in the baseline models to >60% (Figure 13). Reducing habitat by 20% every 10 years resulted in a greater population decline, as expected. Final abundance of females decreased by >60% from baseline models (Figure 12). The increase is risk was substantial; the probability of a 25 % population decline increased from 0 in the baseline model to 1, and there was a 0.92 probability of a 50% decline(Figure 13).

Perturbation- When K was decreased by 10% at the 10 year time step and restored in the following time step, it took approximately 5 years to return to original abundance (Figure 14). Risk of a decline did not substantially increase compared to the baseline model (Figure 15).

When K was decreased by 20% at the 10 year time step and restored in the following time step, it took approximately 9 years to return to original abundance (Fig. 14). Risk of a decline of 10% was increased from <1% to almost 10% (Figure 15).

Density Dependence- For all density dependence types modeled (ceiling, contest, and scramble), mean abundance was the same, which is expected because all models were using the same K value (Figure 16). However, while exponential growth lowered overall risk, using contest or scramble density dependence increased risk of population decline compared to assuming ceiling density dependence (Figure 17).

DISCUSSION

Assessing the vulnerability of species is critical in conservation. Conservation biology is inherently a crisis discipline with limited resources; this makes rapid assessment tools such as population viability analysis (PVA) useful for modeling risk under various potential scenarios. While caution in the use of PVA is warranted (Beissinger & Westphal 1998; Reed et al. 2000), it is a valuable tool as long as the limitations of the model and the assumptions used in model construction are clearly stated (Akçakaya & Sjogren-gulve 2000; Burgman 2000). While PVA models are difficult to test when constructed, they can be evaluated retrospectively. Brook et al. (2000) used 21 long term ecological studies to test the predictive accuracy of PVA by using the first half of each data set to construct the model, and using the second half to evaluate the accuracy of the model. They found models were relatively accurate: no significant bias was observed and modeled risk of decline and abundance projections matched observed outcomes. Evaluations of the predictive accuracy of PVA published since this work have consistently supported its use, especially when used as a relative, rather that absolute, predictor (Ball et al. 2003; Lindenmeyer et al. 2003; McCarthy et al. 2003). Extending its utility by combining it with other approaches such as reserve selection algorithms and decision analysis have also been proposed (Carroll et al. 2003; Drechsler & Burgman 2004).

Our primary objective was to use PVA to assess relative risk for the Crested Caracara in Florida, as well as determine which parameters had the greatest impact on population viability. The demographic growth rate in our model suggested that the population is stable under existing conditions, and is likely limited by habitat or other extrinsic factors, rather than demographic potential. Our perturbation scenarios indicated that this population is relatively resilient, and is able to respond to a restoration of habitat quickly, if conditions are suitable. The time needed to recover was proportional to the magnitude of the perturbation: e.g., a 10% one time reduction in K showed recovery in approximately 5 years, while a 20% one time reduction in K showed recovery in approximately 9 years. In these models, reductions in K were used as a proxy for habitat loss. However, these results could indicate the potential response of this population to other scenarios such as disease or other catastrophes.

Sensitivity analysis conducted by varying all survival and fecundity parameters showed that adult survival had the greatest impact on population persistence, indicating that protection of breeders and their nesting locations is crucial for this population. Adult survivorship has been shown to have the greatest impact on population persistence in a variety of bird species (e.g. Awkerman et al. 2006; Johnson & Braun 1999; Larson et al. 2000; Root 1998) and across taxa including reptiles (Brooks et al. 1991; Heppell et al. 1996), fishes (Morita 2002) and mammals (Kelly & Durant 2000; Wittmer et al. 2005). Interestingly, the 3-stage model showed that a 10% decrease in survival of the adult breeding stage resulted in a consistent decline in abundance.

This pattern was not observed in the 4- and 5-stage models, when the survival of the final stage (experienced breeders) was similarly reduced. This suggests that any scenario that negatively impacts the survival of all breeders will result in an overall population decline; however, if only experienced breeders are impacted, reproduction by the younger breeders mitigates the negative impacts.

Overall, we found little difference among the differently structured models with regard to risk of population decline across scenarios. In the 3-stage model we saw that the adult stage had the largest impact on population persistence, and in the models where inexperienced and experienced breeders were separated, we saw that experienced breeders were more important than their inexperienced counterparts. However, this is not necessarily useful from a conservation perspective. For management, the age of breeders is generally unknown and individuals are not likely to be prioritized or managed differently based on age. Because of this, we chose to use the simpler 3-stage model that makes no assumptions as to different reproductive capability with age or within-stage differences on survival, thus using the often proposed Ockham's razor approach to PVA (Beissinger & Westphal 1998; Morris & Doak 2002). While a more complex model may be able to better identify the role of more detailed life stages if that data are available, this parsimonious model still effectively allowed us to look at the relative impact of habitat loss and perturbation over time on population risk of decline, as well as assess current status under current conditions.

In keeping with this parsimonious approach, we advocate ceiling density dependence in our models because it makes no assumption as to the population's response to changes in abundance. When we compared models using different density dependence types, we found that the model using ceiling density dependence had a lower estimate of risk of decline than either the contest (Beverton-Holt) or scramble (Ricker) models. Which density dependence type is most realistic for Caracaras in Florida is currently unknown. We support the use of ceiling density dependence as a conservative modeling approach; however, this comparison showed that if Caracaras are subject to either scramble or contest competition, the risk for this population could be substantially higher than the more parsimonious model.

These models could be improved, however, with additional field data focused in specific areas. As stated above, the type of density dependence that Caracaras experience could have a substantial impact on risk of population decline. While density dependence is often difficult to determine, this may be a worthwhile focus of research effort. In addition, determining if the increase in survival observed between juveniles and adults is due simply to age or lifestyle is an important next avenue of research. Caracaras are gregarious and nomadic as juveniles, and have been observed in mixed species flocks of more than 30 individuals (Morrison 1996). This is in sharp contrast to behavior as adults, when Caracaras become territorial, highly intolerant of conspecifics, and exhibit strong site fidelity. When habitat is lost, potential breeders may remain in the nomadic juvenile flocks. If survival is due to an increase in mortality conferred by remaining in these flocks, our adult stage survival rate could be substantially lowered, thus greatly increasing risk of population decline. While our models indicated that juvenile survival is less important to population persistence than that of adults, assessing the composition of individuals in these flocks could be critical to understanding how territory or habitat limitations affect adult survival and recruitment.

Our results suggest that the Caracara in Florida is probably not limited by demographic factors such as fertility and mortality, but by other constraints such as habitat. Habitat loss and fragmentation as a primary limitation on populations constitute an all too common pattern for many species (Hoekstra et al 2005), in particular other grassland bird species such as the Sage Grouse (Johnson & Braun 1999), and the Florida Scrub-Jay (Root 1998). Although our baseline population models indicate this population is currently stable, this result assumes that current conditions on the landscape will persist, which is unlikely based on the increasing pressure of development in Florida. Studies on the species thus far also suggest that nesting habitat may be limiting, focusing on the need for more attention to habitat as the primary conservation goal. In addition, our model shows that adult survival has the highest impact on population persistence for this population, thus supporting the current research and management focus on habitat conservation, and specifically adult territories.

Table 1. Model parameters used to develop the 3-stage baseline model for the Crested Caracara in Florida (From Morrison 1998, 1999, 2003, and pers. comm.; stable age distribution is assumed)

Parameter	Value
Replications	1000
Time (years)	50
Age at first breeding	3
Sex ratio	50:50
Proportion of breeding adults attempting breeding/year	0.97-1
Proportion of breeders attempting a second clutch/year	0.15
Mean clutch size for single brood	2.30
Mean clutch size for 1st of 2 broods	2.50
Mean clutch size for 2nd of 2 broods	1.86
Mean hatching success for first broods	0.90
Mean hatching success for second broods	0.64
Survival to independence (~4 months) for first or single clutch	0.57
Survival to independence (~4 months)f or second clutch	0.50
Proportion of yearling from first or single clutch	0.9
Proportion of yearling from second clutch	0.1
Mean monthly survival of juveniles	0.97
Mean annual survival of breeding females	0.91
Stable Age Distribution	Yes
K (females)	500
Initial Abundance (females)	400

Table 2. Parameters used to calculate and differentiate fecundity values for the juvenile breeders (ages 1-3 in the 3- and 4-stage models, and age 2-3 in the 5-stage model), inexperienced breeders (ages 3-5), and experienced breeders (age 5+).

	Proportion of females single brood	Proportion of females second brood	Hatching success for single brood	Hatching success for 1st of 2 broods	Hatching success for 2nd of 2 broods
Juvenile Breeders	0.03	0.00	0.80	0.80	N/A
Inexperienced Breeders	0.80	0.10	0.85	0.85	0.62
Experienced Breeders	0.95	0.15	0.92	0.92	0.63

Table 3. Stage matrix for the 3-stage baseline model for the Crested Caracara in Florida. Top row shows mean annual fecundity contribution for each life stage, all other values show mean annual survival from one stage to the next.

	Yearling (0-1)	Juveniles (1-3)	Adult (>3)
Yearling (0-1)	0	0.031	1.02
Juveniles (1-3)	0.44	0.463	0
Adult (>3)	0	0.231	0.885

Table 4. Stage matrix for the 4-stage baseline model for the Crested Caracara in Florida. Top row shows mean annual fecundity contribution for each life stage, all other values show mean annual survival from one stage to the next.

	Yearling (0-1)	Juveniles (1-3)	Inexp. Breeders (3-5)	Exp. Breeders (>5)
Yearling (0-1)	0	0.028	0.852	1.14
Juveniles (1-3)	0.44	0.463	0	0
Inexp. Breeders (3-5)	0	0.231	0.576	0
Exp. Breeders (>5)	0	0	0.288	0.906

Table 5. Stage matrix for the 5-stage baseline model for the Crested Caracara in Florida. Top row shows mean annual fecundity contribution for each life stage, all other values show mean annual survival from one stage to the next.

	Yearling (0-1)	First Year Juv. (1-2)	Second Year Juv. (2-3)	Inexp. Breeders (3-5)	Exp. Breeders (>5)
Yearling (0-1)	0	0	0.028	0.852	1.14
First Year Juv. (1-2)	0.44	0	0	0	0
Second Year Juv. (2-3)	0	0.613	0	0	0
Inexp. Breeders (3-5)	0	0	0.738	0.582	0
Exp. Breeders (>5)	0	0	0	0.29	0.906

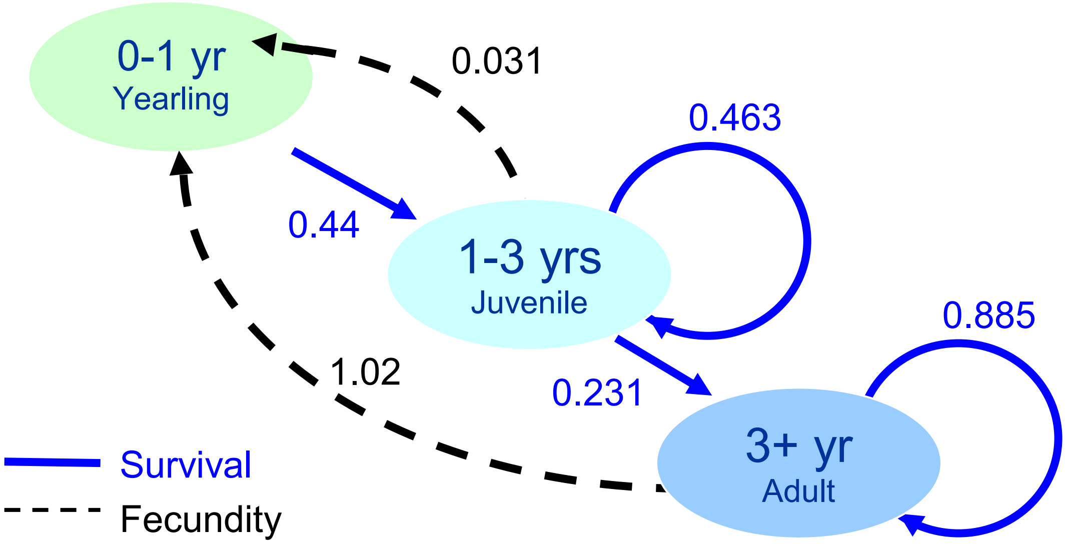

Figure 1. Transitions between stages and survival and fecundity values for each stage in the 3-stage baseline population viability model for the Crested Caracara in Florida. Blue lines indicate mean probability of survival from one stage to the next, dashed lines show each stage's mean fecundity contribution.

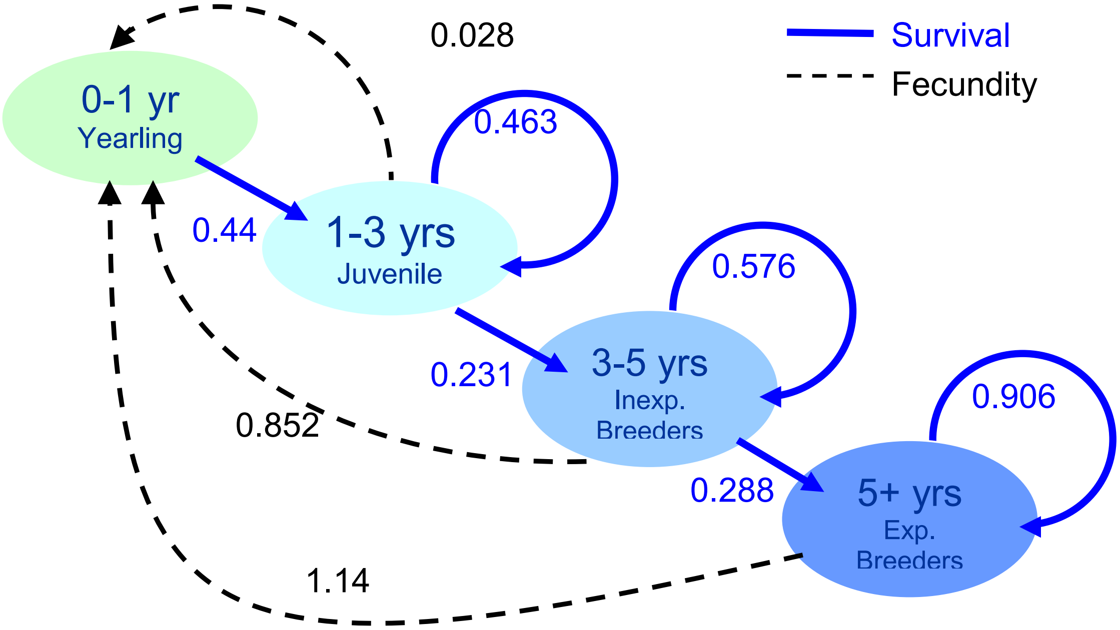

Figure 2. Transitions between stages and survival and fecundity values for each stage in the 4-stage baseline population viability model for the Crested Caracara in Florida. Blue lines indicate mean probability of survival from one stage to the next, dashed lines show each stage's mean fecundity contribution.

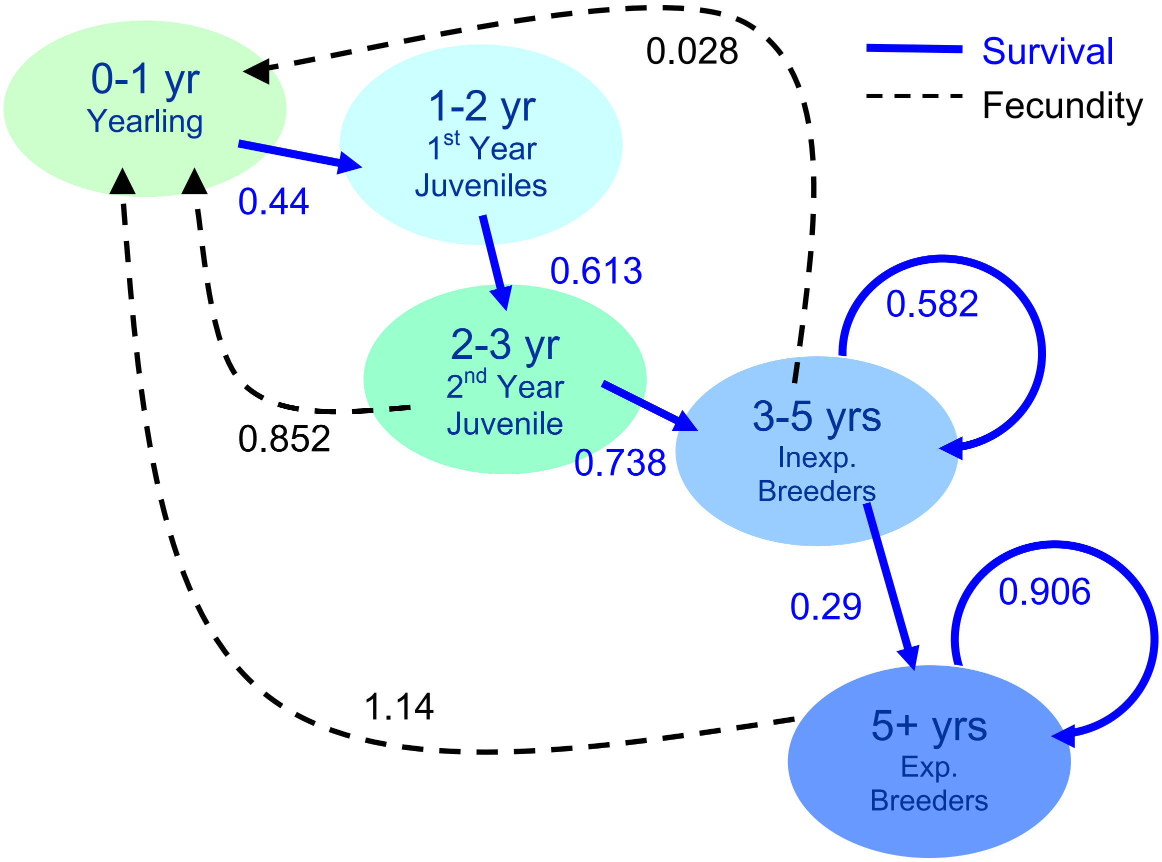

Figure 3. Transitions between stages and survival and fecundity values for each stage in the 5-stage baseline population viability model for the Crested Caracara in Florida. Blue lines indicate mean probability of survival from one stage to the next, dashed lines show each stage's mean fecundity contribution.

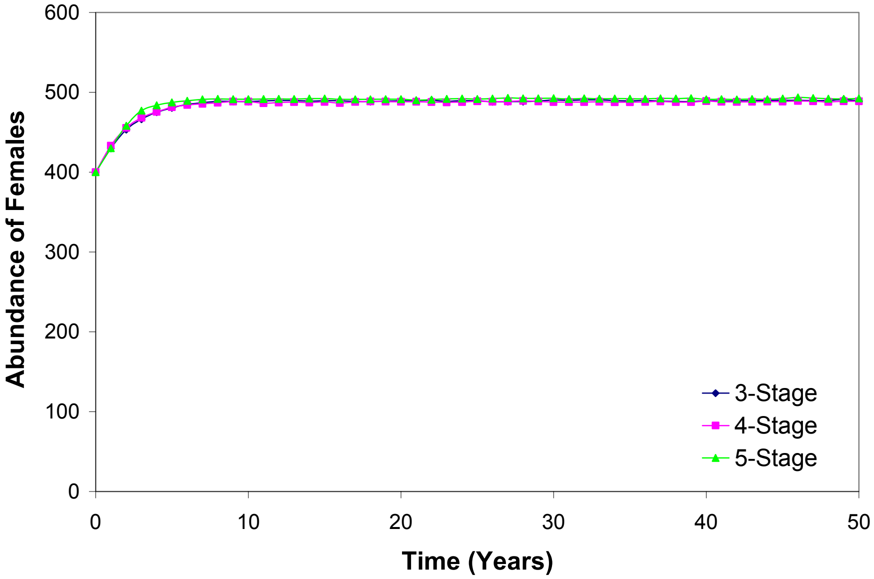

Figure 4. Mean final abundance of female Caracaras in Florida over the 50 year simulation comparing 3-stage, 4-stage, and 5-stage baseline population models.

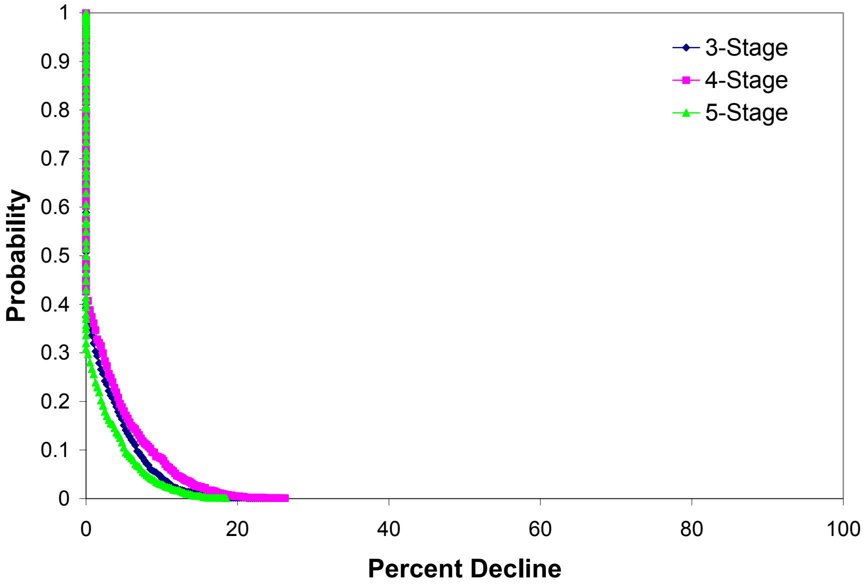

Figure 5. Probability of a percent decline in abundance of female Caracaras in Florida over the 50 year simulation comparing 3-stage, 4-stage, and 5-stage baseline population models.

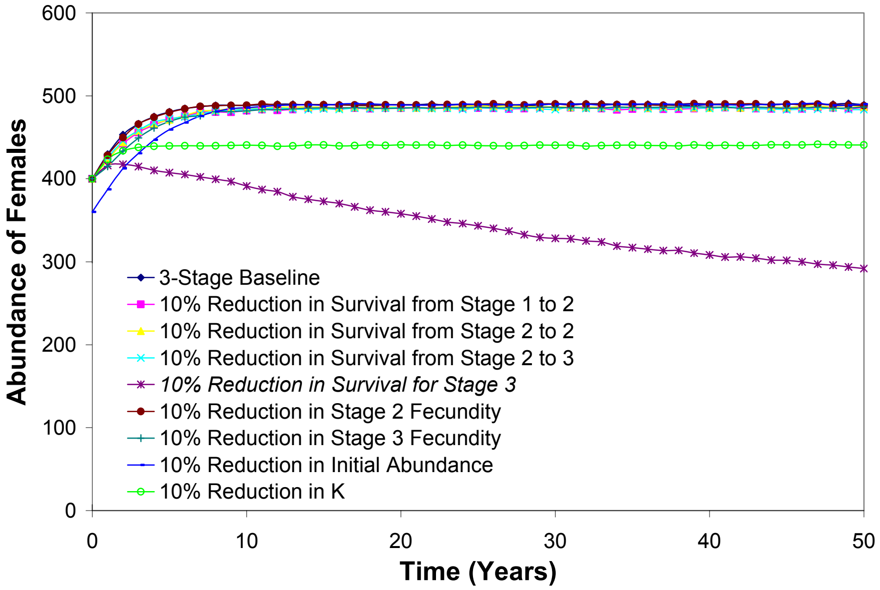

Figure 6. Mean final abundance of females over the 50 year simulation using 3-stage baseline model and 10% reductions in survival and fecundity values for each stage, carrying capacity (K), and initial abundance.

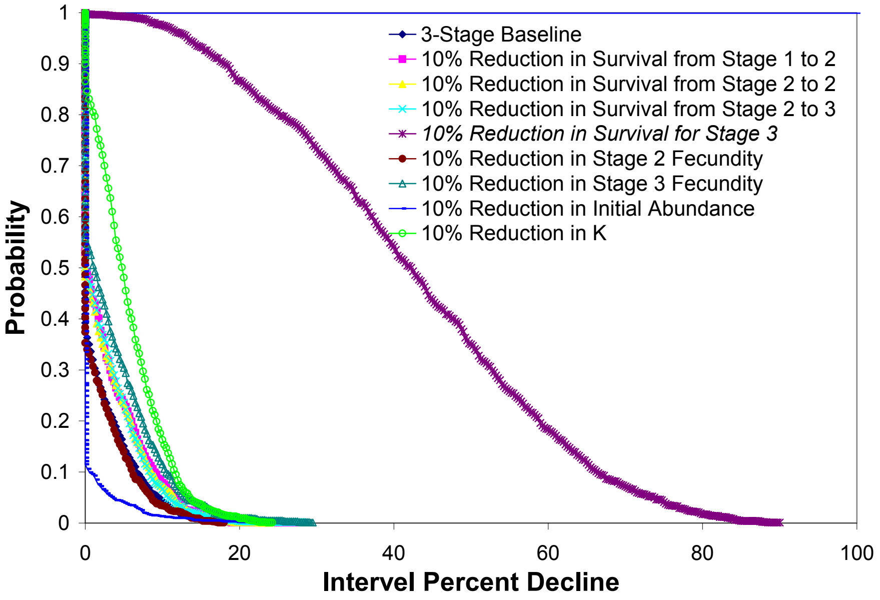

Figure 7. Probability of a percent decline in abundance over the 50 year simulation using 3-stage baseline model and 10% reductions in survival and fecundity values for each stage, carrying capacity (K), and initial abundance.

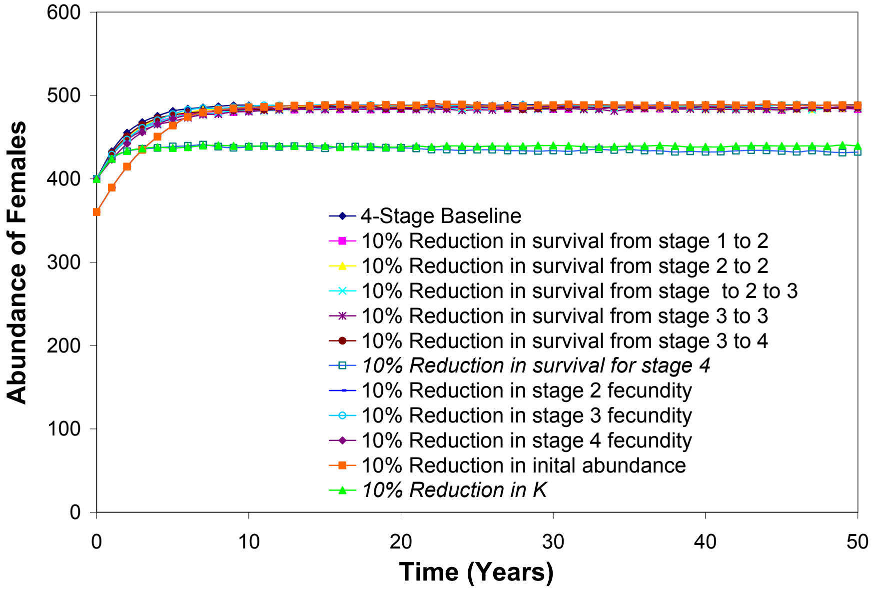

Figure 8. Mean final abundance of females over the 50 year simulation using 4-stage baseline model and 10% reductions in survival and fecundity values for each stage, carrying capacity (K), and initial abundance.

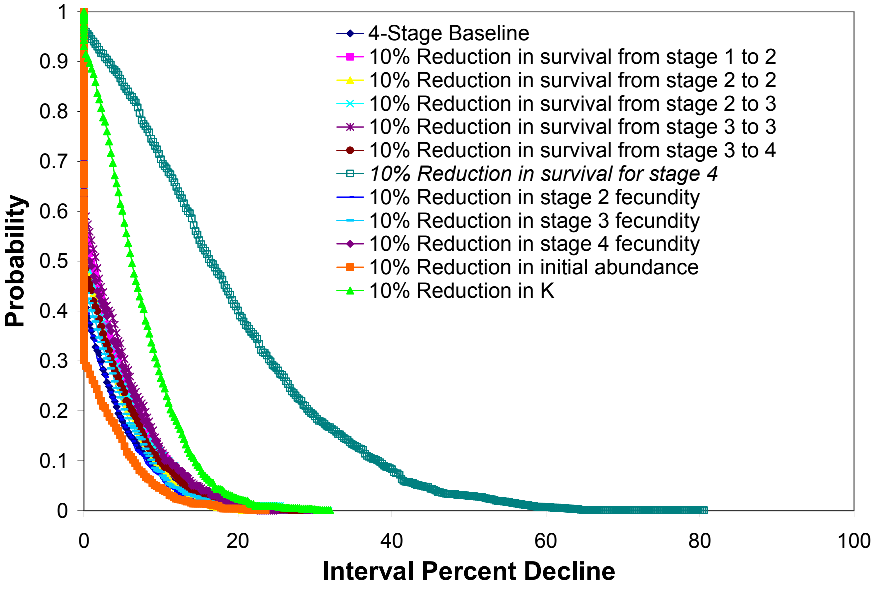

Figure 9. Probability of a percent decline in abundance over the 50 year simulation using 4-stage baseline model and 10% reductions in survival and fecundity values for each stage, carrying capacity (K), and initial abundance.

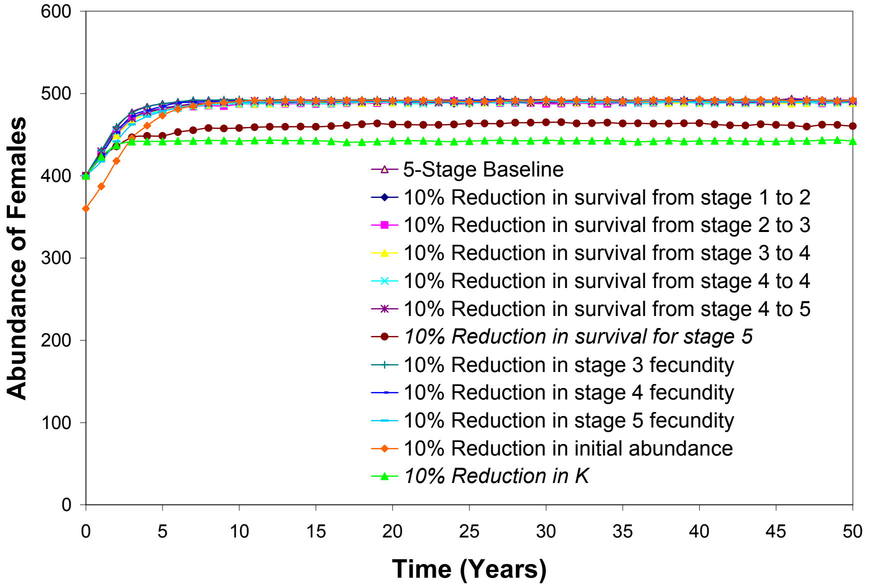

Figure 10. Mean final abundance of females over the 50 year simulation using 5-stage baseline model and 10% reductions in survival and fecundity values for each stage, carrying capacity (K), and initial abundance.

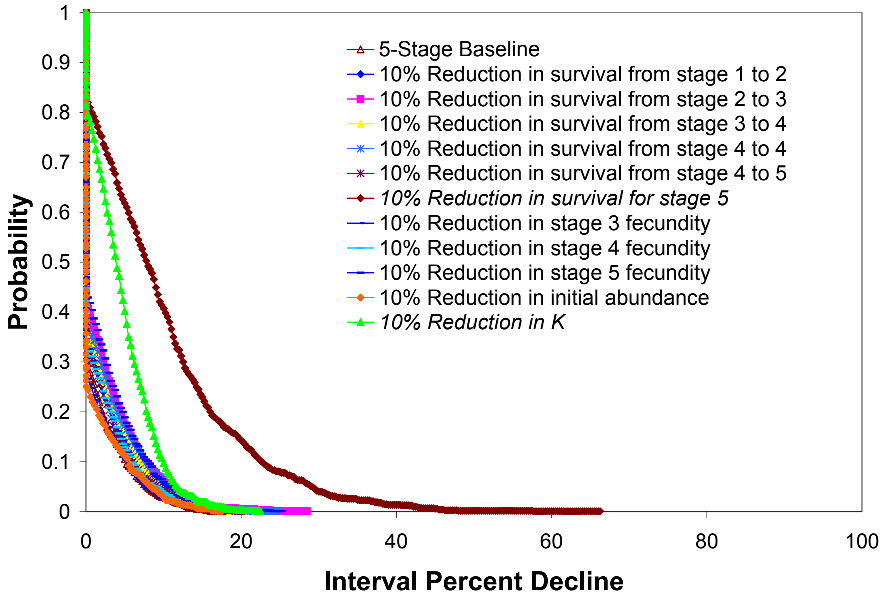

Figure 11. Probability of a percent decline in abundance over the 50 year simulation using 5-stage baseline model and 10% reductions in survival and fecundity values for each stage, carrying capacity (K), and initial abundance.

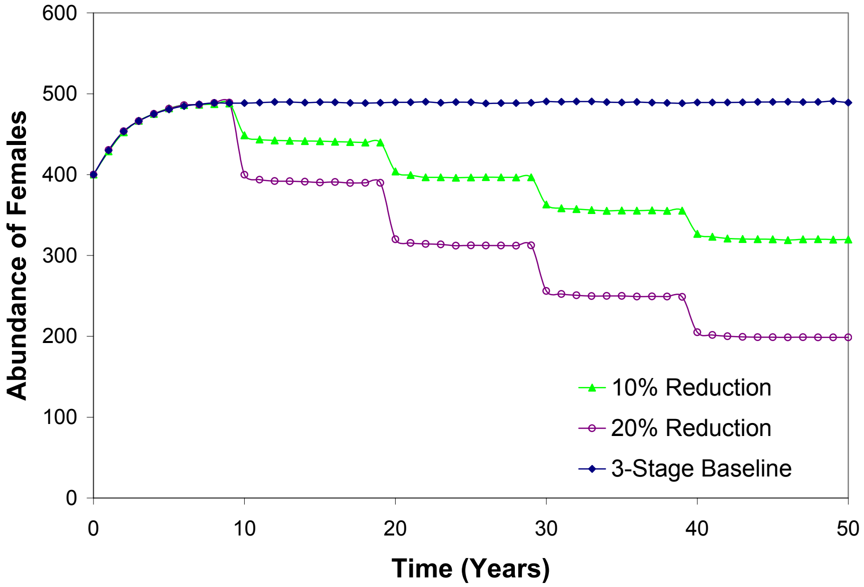

Figure 12. Mean final abundance of females over the 50 year simulation comparing 3-stage baseline model to two scenarios of an iterative reduction of habitat each 10 years by 10% and 20%, respectively.

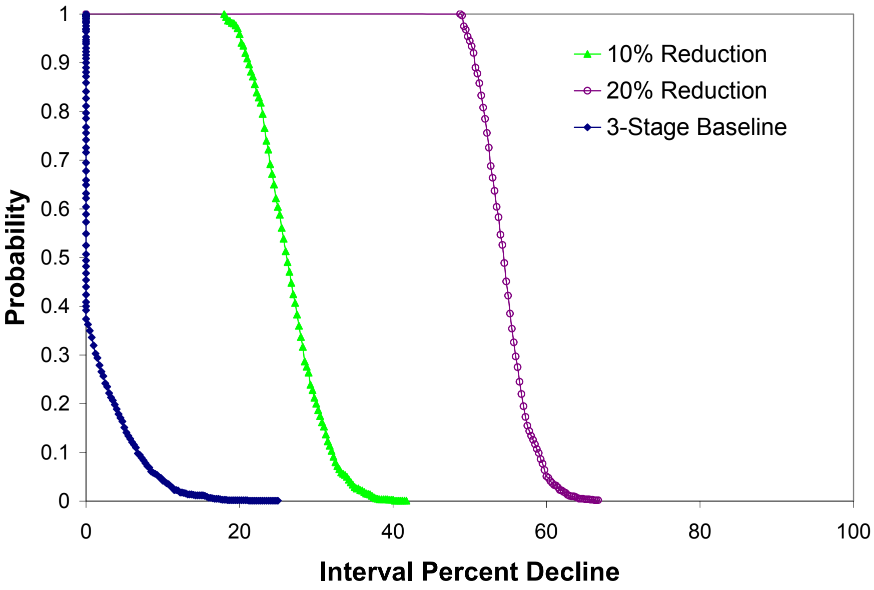

Figure 13. Probability of a percent decline in abundance over the 50 year simulation comparing 3-stage baseline model to two scenarios of an iterative reduction of habitat each 10 years by 10% and 20%, respectively.

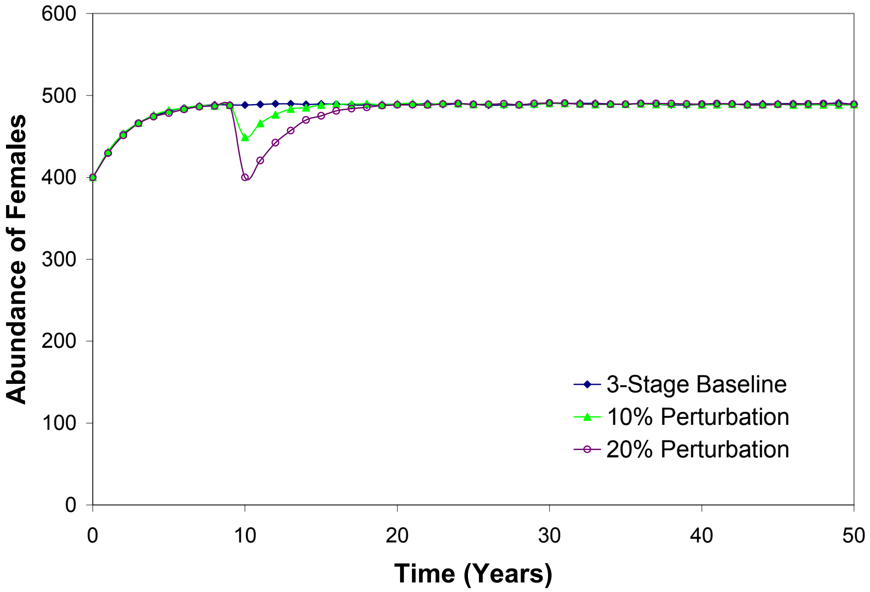

Figure 14. Mean final abundance of females over the 50 year simulation comparing 3-stage baseline model and two scenarios of a 10% and 20% perturbation (modeled by a decrease in carrying capacity) at 10 years.

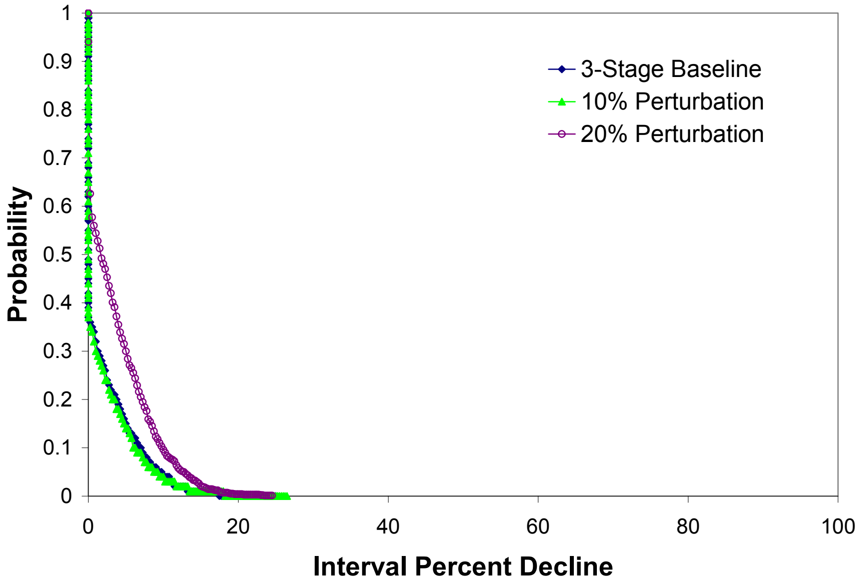

Figure 15. Probability of a percent decline in abundance over the 50 year simulation comparing 3-stage baseline model and two scenarios of a 10% and 20% perturbation (modeled by a decrease in carrying capacity) at 10 years.

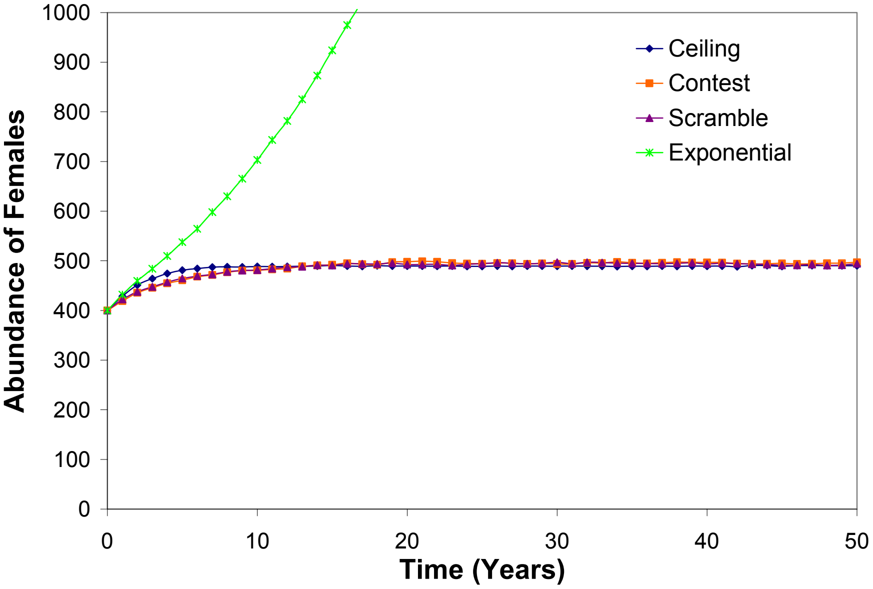

Figure 16. Mean final abundance of females over the 50 year simulation comparing 3-stage baseline model using ceiling density dependence to models using Contest density dependence (Beverton-Holt), Scramble density dependence (Ricker), and exponential growth.

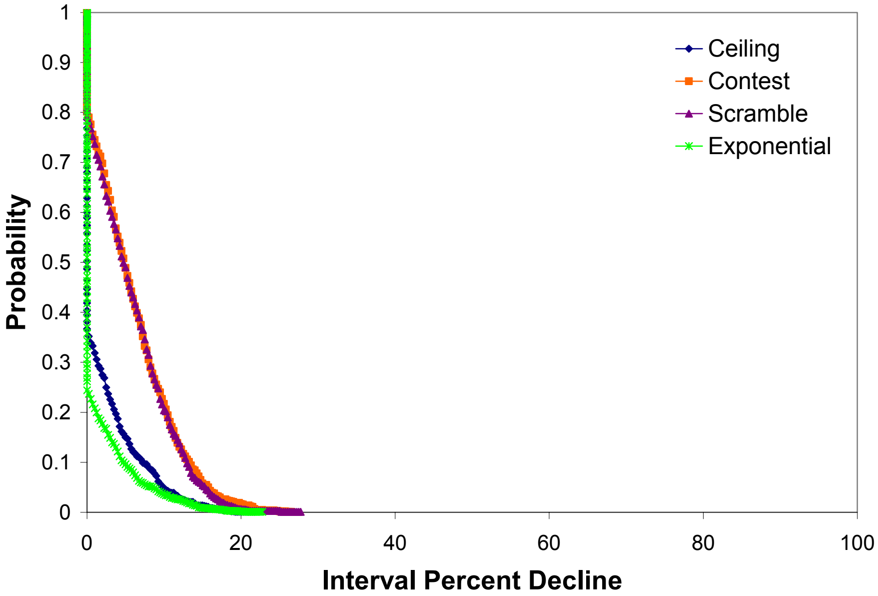

Figure 17. Probability of a percent decline in abundance over the 50 year simulation comparing 3-stage baseline model using ceiling density dependence to models using Contest density dependence (Beverton-Holt), Scramble density dependence (Ricker), and exponential growth.

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CHAPTER III

PREDICTING HABITAT DISTRIBUTION FOR THE CRESTED CARACARA (*CARACARA CHERIWAY*) USING A SPATIAL MODELING APPROACH

INTRODUCTION

Understanding the habitat requirements for species or populations at risk is critical for effective conservation management (Brambilla et al. 2006; Clark et al.1993; Gibson et al. 2004). Mitigation, restoration, and prioritizing land management and acquisition all require at least a basic understanding of the habitat needs of the species of interest. Ideally, one would survey the entire range of a population to determine the ecological characteristics necessary; however, this is rarely logistically feasible. Accurately characterizing habitat is even more difficult for species that are cryptic, range widely, or occur in habitats where access by researchers is restricted (Guisan et al. 2006; Osborne et al. 2001; Rushton et al. 2004).

Habitat modeling using Geographic Information Systems (GIS) alleviates many of these difficulties, and has been shown to characterize habitat use effectively as well as predict potentially suitable habitat (Clark et al. 1993; Gibson et al. 2004; Guisan & Zimmermann 2000; Raxworthy et al. 2003; Thompson et al. 2006). The various statistical methods commonly used to build predictive habitat models can be divided into two main groups based on data requirements: those that require presence/absence data as a response variable for model development [e.g. logistic regression, general additive models (GAM), Artificial Neural Networks] and those that require only presence data [e.g. Ecological Niche Factor Analysis (ENFA), the Mahalanobis Distance (D^2) Statistic], and the advantages and limitations of these various methodologies have been widely discussed (Brotons et al. 2004; Corsi et al. 2000; Fielding & Haworth 1995; Guizan & Zimmermann 2000; Hirzal et al. 2001, Knick & Rotenberry 1998). Ultimately, the statistical method used to build a particular model, the type of data used for model development, and a species' ecological characteristics can influence the predictive performance of the resulting model. While these issues should all be taken into account when choosing a statistical method, the type of data available often limits what specific method can be used.

A common limitation in developing a predictive habitat model for many species is the availability of reliable absence data. Absence of individuals may be inaccurate for a variety of reasons. Potential problems with absence data include generating false negatives that can occur when areas have not been adequately surveyed, individuals are present but are not detected, or when habitat is actually suitable but currently unused for other reasons, e.g., low population size (Browning et al. 2005; Clark et al. 1993; Duncan & Dunn 2001). Inadvertently using false negatives or generating pseudo-absences may negatively impact discrimination between used and unused sites in model development. Therefore, the use of presence/absence data is often inadvisable.

The Mahalanobis (D^2) is appropriate for cases lacking absence data, thus resolving these difficulties. This statistical method calculates an "ideal" habitat based on presence locations and then calculates how distant each location in the area of interest is from this ideal. Mahalanobis (D^2) has been used effectively for GIS-based habitat modeling for a variety of species including mammals (e.g., Clark et al. 1993; Corsi et al. 1999; Knick & Dyer 1997), reptiles (e.g., Browning et al. 2005), and birds (e.g., Rotenberry et al. 2006).

Although habitat models can be useful for understanding species' ecological requirements, they are only useful for species that use habitat selectively. The most common method for determining selectivity is to compare the ecological variables at used locations to those available throughout the range of the species or within a defined study area (Alldredge & Ratti 1992; Manly et al. 1993). However, Katnik and Wielgus (2005) found that Type I error rates were ≥0.24 when using this traditional method. This error rate was not reduced when the number of animals surveyed was increased nor when the number of habitat types was decreased, both of which are methods commonly used to increase accuracy in detecting habitat selection. Comparing randomly distributed simulated home ranges to actual home ranges was found to reduce this error rate significantly (Katnik & Wielgus 2005).

Here, we present a modeling approach that uses the most commonly available data, presence of individuals, to build a predictive habitat model using raster data in a GIS and the Mahalanobis Distance (D^2) Statistic. To determine which ecological variables we incorporate in our model, we use the method proposed by Katnik and Wielgus (2005) to test the significance of each ecological variable available as GIS data; this reduces type I error and our reliance on a priori assumptions of which variables should be included in model development.

Our research focuses on Florida's population of the Crested Caracara (*Caracara cheriway*), a medium-sized raptor that occurs in the south-central peninsula. This population is currently listed as threatened at the state and federal levels. Caracaras face threats similar to those faced by many other species of conservation concern: small population size, geographic isolation, habitat loss and degradation due to an increasing human population, and a high dependency on private landowners; more than 80% of known nesting territories occur on private lands (Morrison & Humphrey 2001). Difficulty in accurate determination of absences due to inaccessibility of privately-owned lands makes using a presence-only method like the Mahalanobis (D^2) ideal for this population. We use our modeling approach to develop a predictive habitat suitability map for this Caracara population across its entire range in Florida.

Study Species

The Florida population of the Crested Caracara is disjunct from the species' larger range, which extends from extreme southern Texas and Arizona through Mexico and into northern South America (Morrison 1996). The Caracara was formerly documented as inhabiting native prairie in Florida (Nicholson 1929; Howell 1932), but population numbers and the extent of historic nesting activity throughout the state are not known. Currently, Caracaras are associated with open grassland, including cattle pasture and the dry prairie ecosystem (Morrison & Pias 2006, Abrahamson & Hartnett 1990). Caracaras presumably require open areas for hunting and trees for nesting, but little else is known about what specific habitat features they require (U.S. Fish and Wildlife Service 1999; Morrison & Humphrey 2001).

Because many nest sites currently occur on private lands, obtaining an accurate estimate of population size is impossible, and monitoring known nesting territories is problematic, as well. As a result, population status is difficult to ascertain, though the population is currently thought to be in a long-term decline (Millsap et al. 1990; Layne 1996). Conversion of dry prairie has occurred throughout much of the Caracara's range first to ranching and agriculture and, more recently, to urban development. Particularly in the last 10 years, land use patterns have changed dramatically throughout south-central Florida as land prices have escalated. Current trends predict that future habitat loss and conversion in Florida will continue to occur in dry prairie and flatwood ecosystems (Morrison & Pias 2006).

To better understand the current status of this species and predict the impacts of future changes in land use on the population, methods are needed to characterize and identify suitable habitat across the landscape. This information is necessary to inform mitigation and recovery efforts, as well as for targeting areas for protection or restoration. Here, we present a framework to build a habitat suitability model for this species. Our framework is also applicable to other wide-ranging species that may be prone to errors of omission during traditional surveys and for which little information on specific historic and current habitat use is available.

METHODS

Study Site

Our study area included much of central peninsular Florida: east to west across the peninsula between both coasts, with the northernmost point in Seminole County, and the southernmost in Miami-Dade County (Figure 1). These boundaries were selected because this area encompasses all documented Caracara observations from several datasets and thus represented the best estimate of the current geographic range of the species in Florida. These datasets included known nest sites identified through field research (Morrison 1999; Morrison & Humphrey 2001), all radio telemetry locations collected on radio-tagged Caracaras during 1994-2000 (J. Morrison unpublished data), and two datasets of Caracara observations: the Florida Fish and Wildlife Conservation Commission's Nongame Wildlife Program's Wildlife Observation Database and Florida Natural Areas Inventory occurrence records (Anonymous 2006). We wanted to be sure the study area encompassed all known Caracara locations plus an additional area defined by adding 40 km, the longest known natal dispersal distance (Nemeth & Morrison

2002), to all locations at the outermost extent of these datasets. The study area totaled approximately 59,980 km^2 in size.

Historically dominated by pine flatwoods and dry prairie (Abrahamson & Hartnett 1990), most of the study area is now characterized by large open expanses of grasslands dotted with numerous shallow ponds, wetlands, and marshes and scattered or small clumps of live oaks (*Quercus virginiana*), cabbage palms (*Sabal palmetto*), pine (*Pinus spp*.), and cypress (*Taxodium spp*.). The landscape in this region is a mosaic of habitats that reflects complex patterns of land ownership and uses. More than 70% of the land is in private ownership. Principal land uses on private lands include cattle grazing and agricultural production of citrus, sugar cane, and other crops. Lands in state and federal ownership are managed primarily as natural areas (no agricultural production and limited livestock grazing) to support native plant and animal communities.

Overview of Modeling Approach

In our model development, we used a dataset of 28 Caracara nest locations and associated home ranges estimated using radiotelemetry (Morrison & Humphrey 2001) along with a variety of GIS data. Land cover, lentic water, and urban area data were obtained from the Florida Vegetation and Land Cover layer (FWC 2003); road data were obtained from the Florida Department of Transportation (FDOT 2002); and lotic water data were obtained from the National Hydrography Dataset (USGS 2005). Metadata on the underlying construction of these layers and their descriptions are available from the sources of each layer used (Table 1). Analyses utilized raster data with 30 m resolution. Vector data, such as roads and lotic water, were converted to raster data with each cell containing the value of either the distance to the nearest feature (e.g., distance to nearest road) or the density of features (e.g., density of roads) within a specified neighborhood equal to an average Caracara home range (approximately12.04 km^2, Morrison & Humphrey 2001). Our approach consisted of three steps, described in detail below: (1) statistical analysis of the home ranges; (2) development of predictive models of habitat suitability; and, (3) evaluation of the models using an independent dataset of Caracara locations. We conducted all spatial analyses using ArcView 3.x and 9.x (ESRI, Redlands, California, USA). Statistical analyses were completed using Minitab v. 13 (State College, Pennsylvania, USA).

Statistical analysis of home ranges

The first step in determining suitable habitat for a species is to examine the range of values for environmental variables in areas of occupancy (Corsi et al. 2000) then to compare these values to those found across the landscape. We characterized each of the 28 known home ranges for each of the ecological variables using Hawth's Tools (Beyer 2004). The ecological variables analyzed included all 43 vegetation and land cover classes from the Florida Vegetation and Land Cover layer, and additional variables such as density of roads and lotic water, number and total area of lentic waterbodies, and distance to urban areas (both high and low impact) (Table 1). To normalize for difference in home range area, we converted the amount of each land cover type to a proportion of the total home range area. For each data layer, we reclassified the raster cells to contain the value of the sum of the total amount of that ecological variable within a moving window 12.04 km^2 in size. In the habitat models, therefore, the suitability of each 30 m cell may be thought of as a prediction of that cell's suitability as the center of a hypothetical circular home range having an area of 12.04 km^2. We used this method as a way of assessing the value of each raster cell as habitat in the context of its surrounding area.

As land cover types are often not randomly distributed across the landscape, composition of the home ranges was compared to that of simulated (randomly generated) home ranges (Katnik & Wielgus 2005). A total of 962 simulated home ranges of 12.04 km^2 were randomly distributed across the study area. Composition of the simulated home ranges was characterized using the same method used on actual home ranges. We compared the compositions of the 28 actual home ranges to 28 randomly chosen simulated home ranges iteratively, using a bootstrap method. To avoid assumptions of normality, we used the non-parametric Mann-Whitney statistic to determine whether significant differences in composition occurred between the actual and the simulated home ranges, testing each variable separately. Only those ecological variables found to be significantly different in value between actual and simulated home ranges ($P < 0.05$) were selected for incorporation into the habitat suitability models. These preliminary statistical analyses were used to determine which layers would be used in constructing our model, thus eliminating any a priori assumptions of what habitat characteristics were important for the species.

Development of the Habitat Model

To develop the habitat suitability models, we used occurrence data for Crested Caracaras in Florida consisting of GIS vector files of the 28 home ranges and associated nests. We constructed Mahalanobis models for the Caracara using the Mahalanobis distance extension for ArcView 3.3 (Jenness 2003). Only those GIS layers containing ecological variables found in significantly different proportions in actual versus simulated home ranges were incorporated into the model. Point data are required for calculation of the ideal habitat, so we used two data sets to construct two separate models: point data of actual nest sites within home ranges and point data representing the geographic centers of the home ranges. We did this to determine how home range shape and location of the nest within the home range would affect the accuracy of the resulting habitat model. In order to normalize the resulting output, we converted values to chi-square *P*-values ranging from 0 to 1, with 1 representing the cells most similar to the ideal.

Model Evaluation

To evaluate a predictive habitat model, two things are required. First, one must determine a cut-off where the landscape is classified as habitat or not; second, a set of independent data is needed to test the predictive capability of the model. The former is especially important for management purposes; defining the entire study area as suitable, or using values along a continuous gradient of suitability may be of little value to guide management efforts. If the goal is to focus sampling efforts, choosing a more discriminate cut-off (e.g., one that greatly reduces the amount of study area) may be of value. If conservation is the goal, for example, identifying potential mitigation or suitable restoration habitat, choosing a less discriminate cut-off which includes more of the study area may be useful. The benefits of each should be weighed with the goal of model use.

We chose to use a balanced approach in determining our cut-off value. Identifying the best model from our Mahalanobis (D^2) model results meant choosing a *P*-value that balanced the trade-off between reduction of total study area identified as suitable and accuracy in classification of test nest locations, and using that as the cut-off value. For example, a particularly well-performing model would greatly reduce the amount of area judged suitable, while still accurately classifying a high percentage of the test nest sites as occurring on suitable habitat. We evaluated the resulting models using an independent dataset of 80 known Caracara nest site locations identified throughout the study area (J. Morrison, unpublished data)

After determining the cut-off value for each model, the GIS layers were reclassified so that raster cells with values below the cut-off were reclassified as 0, and those with values above the cut-off were reclassified as 1. This produced final maps with a binary classification of suitability: 0 for unsuitable, 1 for suitable. Suitability for this model was thus defined as areas that contained the ecological characteristics within a determined Mahalanobis (D^2) distance (defined by the cut-off value) from the calculated (D^2) ideal based on known home ranges used in model development.

To further evaluate our predictive habitat suitability models we conducted on-site visits to central Florida in 2006. These visits focused on ground-truthing model results, as well as recording local features that are not represented in our large scale data layers.

RESULTS

Statistical analysis of home ranges

The proportions of cabbage palm-live oak hammock, grassland, improved pasture, unimproved pasture and hardwood hammocks and forest land cover types were higher ($P < 0.05$) in actual home ranges than in simulated home ranges. The density (m/km^2) of lotic (flowing) water was significantly greater in the actual versus simulated home ranges, as was the proportion of lentic (non-moving) water. The density of roads was not significantly different, nor were center points of actual and simulated home ranges significantly different in their distance from roads or urban areas. In all, seven data layers met the criteria for inclusion in the predictive habitat suitability models: cabbage palm-live oak hammock, grassland, improved pasture, unimproved pasture, hardwood hammocks and forest, lentic water, and lotic water (Table 1).

Model Evaluation

We found little difference between the Mahalanobis model constructed using the point data from actual home range nests and the model constructed using the home range center points (Figures 2 & 3). For the Mahalanobis model constructed using nest locations, the cut-off value chosen that balanced the trade-off between predictive accuracy and reduction of total study area was 0.09, which reduced the study area by 75% and accurately classified 75% of nests from the evaluation data set (Figures 4 & 6). The model created using the center points of each home range reduced the study area by 76% and accurately classified 71% of nests from the evaluation data set using the cut-off value of 0.25 (Figures 5 & 7). Our final model combined these two models, and shows three classifications: 0 (meets suitability for neither model), 1 (meets suitability for 1 model), 2 (meets suitability for both models). In this combined model, 81.25% of the test nest sites were located in suitable habitat which accounts for only 27.84% of the study area, a reduction of 72.16% (Figure 8).

Incorrectly classified nests from the evaluation data set (n = 15) showed no tendency to be located in any one portion of the study area. To determine how far away from suitable habitat these incorrectly classified nests were on the landscape, we measured the euclidean distance between incorrectly classified nests to nearest area identified as suitable. We found that 8 of 15 nests were within 1 km of suitable habitat and 10 of 15 were within 2 km. These distances are well within known foraging distances from the nest for the Caracara (J. Morrison, unpublished data).

During ground evaluations in Florida in 2006 we visited areas of predicted suitable habitat that lacked documented Crested Caracara sightings, from either data used in this study or historic records. We looked for habitat characteristics in these areas that appeared different from known Caracara locations but may not have been accurately or precisely delineated by the GIS data. Our observations indicated that the most obvious difference from areas of known occupancy was the low prevalence of cabbage palms.

DISCUSSION

As human population growth expands in Florida, changes to the landscape will continue. Identifying critical parameters that describe suitable habitat for the Crested Caracara in Florida is an important step in ensuring this population's long-term viability. The current project identified seven landscape variables (five types of vegetation/land cover and two types of water) that are significantly associated with presence of Crested Caracaras in the current landscape; our model built using these data successfully predicted the species' occurrence throughout the study area with a high degree of accuracy. Historically, the Caracara was associated with grassland and wetland habitats in Florida (Nicholson 1929). Today, the species appears to be exploiting pastures, ditches, and impounded wetlands that have replaced the historic land cover, as evidenced by the positive association of home ranges with improved pasture, unimproved pasture, and lotic waters.

We found little difference in areas identified as suitable between the two Mahalanobis models constructed using the center points of the home ranges and the nest sites within the home range. This was not unexpected, as these points were usually in close proximity. The final predictive habitat model, a combination of these two models, performed very well in both the percentage of test nests accurately categorized as occurring in suitable habitat (81.25%), and in reducing the area judged suitable (27.84% of the study area). Nests incorrectly classified by the final model did not seem to follow any pattern (i.e., they did not correspond with any specific geographic locations on the map or with the home ranges used to construct the model). This indicates that our model has similar accuracy across the study area and is not biased by the distribution of the data used in constructing the model. However, future research should examine how nesting tree availability may influence nest locations relative to suitable habitat; for example, the majority of our incorrectly classified nests were within foraging distance of suitable habitat. Caracaras may occasionally nest in areas that are less suitable but that contain suitable nesting trees and also have suitable foraging habitat nearby. This would not be surprising given the scattered yet clumped dispersion of potential nest trees at many sites (J. Morrison, pers. obs.).

Our results highlight the complexity of habitats used by the Caracara in Florida. Home ranges are heterogeneous entities in a complex landscape and critical characteristics for the Caracara can be identified at the home range and landscape scales. Our method of recoding each pixel to reflect the context of the habitat surrounding it within an average Caracara home range allows us to incorporate the importance of neighboring areas and their influence on habitat use, which is of particular interest for territorial species where home ranges incorporate multiple units of analysis. In a study on black bears in Arkansas, Clark et al. (1993) adopted a similar approach when they recoded one layer used in their habitat analysis to reflect the number of different habitat types present in a pre-determined moving window. The importance of the surrounding landscape on habitat selection has been found to be important for many bird species (Brambilla et al. 2006; Martin et al. 2006; Saab 1999). The context of the surrounding landscape is often not included in traditional methods of habitat modeling where only the data at the point of presence or absence is included in the analysis.

Presence data are the most commonly available species data and are verifiable, while absence data may be unverifiable, and thus inaccurate for a variety of reasons. Species may be rare or cryptic which may make detection difficult, habitat may be suitable but currently unoccupied for other reasons, or there may be a temporal disjunct between observation and use (Duncan & Dunn 2001; Mackenzie 2006). For the Crested Caracara in Florida, researcher access to private lands can be restricted and these private lands comprise most of their breeding habitat (Morrison & Humphrey 2001), making absence data difficult to obtain. Previous research supports the power of presence-only methods, and specifically the effectiveness of the Mahalanobis (D^2) statistic, for developing species distribution models (e.g. Browning et al. 2005; Clark et al. 1993; Corsi et al. 1999; Knick & Dyer 1997; Rotenberry et al. 2006).

On-site evaluations of the final model serve to reiterate the often cited limitations of predictive models with regard to scale and input data (Austin 2007; Corsi et al. 2000; Guisan & Zimmermann 2000). Examination at a finer scale of sites identified as suitable while having no known Caracara observations revealed that many of these sites lack cabbage palms, the primary tree used for nesting by the Caracara in Florida (Morrison in press). The Florida Vegetation and Land Cover layer used to construct the models lumps this vegetation type into the category "cabbage palm - live oak hammocks" (FWC 2003). Further delineation of this vegetation category to identify cabbage palms specifically may increase the accuracy of these models, but it may not. Cabbage palms utilized by Caracaras are often found in small clumps of only a few trees in a pasture, grassland, or other vegetation type. That these small clumps of trees are unlikely to be captured by classified satellite imagery of 30m resolution is evidenced by the land cover types identified at the 108 Caracara nest locations used in either the development or evaluation of our model. Eleven of the 14 (79%) land cover types (FWC 2003) are typified by few or no trees, including improved pasture, where > 70% of these known nests are located. The scale of the data layer is simply not suitable for delineating these small, yet important, characteristics of the local landscape. It is important also to note that we cannot currently determine why cabbage palms seem to be less common in some areas. While it could be as simple as landowner choices on which trees are kept or cut down, this could also be due to differences among local environments such as soil composition or hydrology.

Further work is needed to assess habitat suitability in areas deemed suitable but lacking records of Caracaras, or in areas where Caracaras currently are found but not deemed suitable in our model. In a study on three forest bird species, Thogmartin and Knutson (2007) found that while landscape features strongly influences habitat selection, birds were being influenced by multiple spatial scales. Supported by this and other studies (Brennen et al. 2002; Holland et al. 2004; Wiens et al.1987), we reiterate the importance of considering habitat associations at multiple scales, and recommend that future research should focus on identifying the local characteristics correlated with Caracara presence at a finer scale. These local characteristics would complement our current landscape-scale model by explaining why certain areas judged suitable show high rates of use, while other areas show low to no use. In addition, understanding these local scale variables may be necessary for mitigation or restoration efforts. Finally, identifying patterns to Caracara distribution across the landscape may aid in prioritization of habitat for conservation.

Our results led to the conclusion that heterogeneity, including specific land cover types and water features, is critical in maintaining suitable habitat for the Crested Caracara in Florida. Our approach allowed us to identify these important habitat characteristics, incorporate the context of the area around each pixel, and define suitable habitat with a high degree of success. For the Caracara in Florida, these results can serve as a guide for restoration, mitigation, and other conservation efforts for this isolated population. However, we believe this modeling framework demonstrates a useful and flexible approach applicable to other species and systems.

Table 1. Data layers and sources used in analysis of Crested Caracara home ranges in south-central Florida (*n* = 28). Those variables found to be positively correlated with Caracara home ranges compared to simulated home ranges are bolded. These variables were used to develop the predictive habitat model.

Layer Name	**Source**	**Description**
Florida Vegetation and Land Cover	Florida Fish and Wildlife Conservation Commission (FWC; 2003)	43 vegetation and land cover classes in Florida. Land cover classes used in predictive model construction: **Cabbage Palm-Live Oak, Grassland, Mixed Hardwood-Pine Forest, Improved Pasture**, and **Unimproved Pasture**
Lotic water	National Hydrography Database for Florida (2005), Florida Department of Environmental Protection	Created by combining all flowing water categories (Artificial Path, Canal/Ditch, Coastline, Connector, Pipeline, Stream/River) then converting to a raster file of the density of lotic water per km^2.
Lentic water	Florida Fish and Wildlife Conservation Commission (FWC) (2003)	Created by combining all standing water habitats in Florida Vegetation and Land Cover Layer (class values: Freshwater Marsh and Wet Prairie, Sawgrass Marsh, Cattail Marsh, Shrub Swamp, Bay Swamp, Cypress Swamp, Mixed Wetland Forest, Hardwood Swamp, Hydric Hammock, Salt Marsh, Mangrove Swamp, Tidal Flat
Urban	Florida Fish and Wildlife Conservation Commission (FWC) (2003)	Created by combining all urban categories in Florida Vegetation and Land Cover Layer (class values: High Impact Urban, Low Impact Urban).
Roads	Florida Department of Transportation (2002)	All roads of Florida

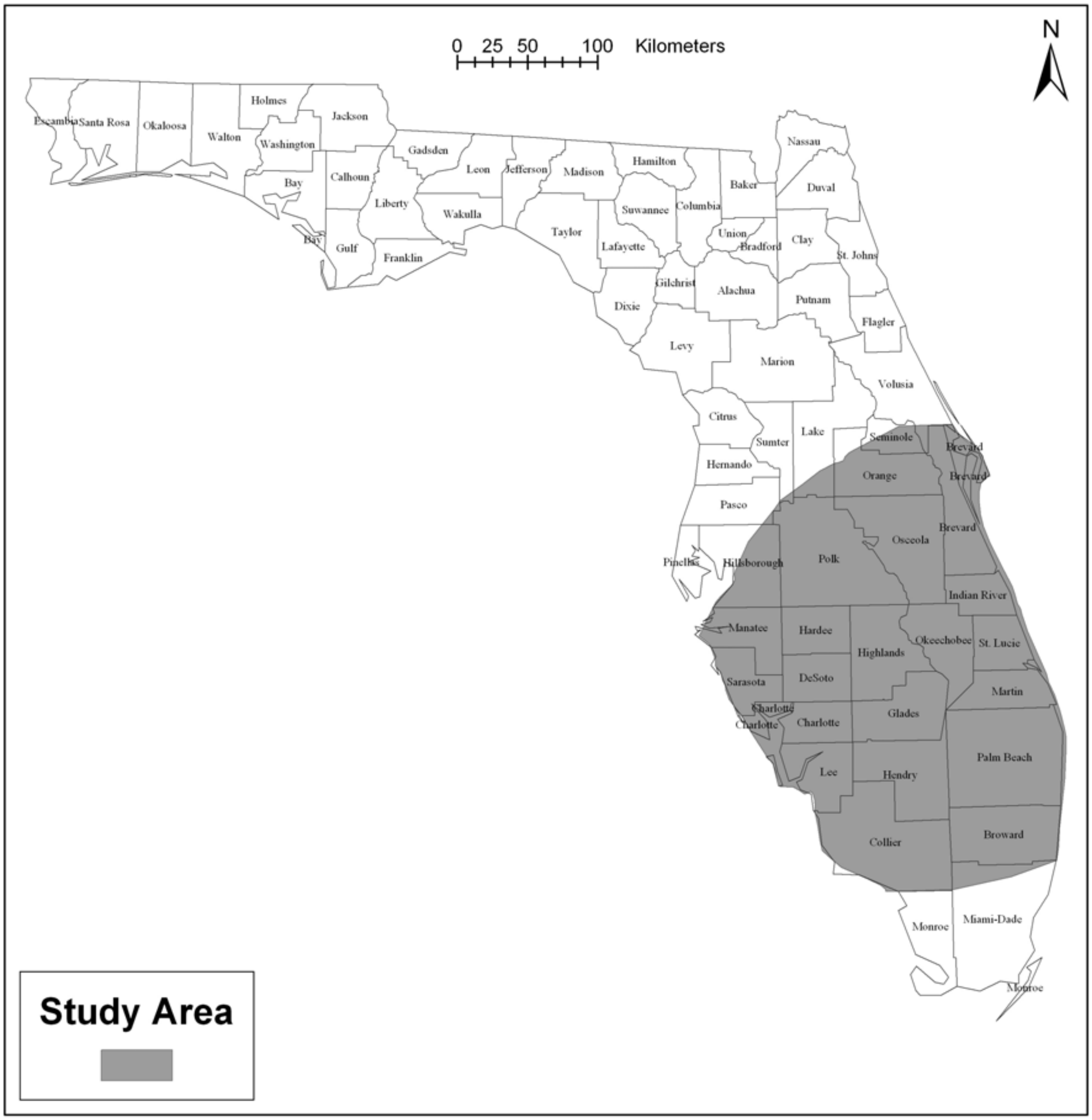

Figure 1. Location of the study area for which we developed the predictive habitat model for the Crested Caracara in Florida. This area represents the best estimate of the current geographic range of the Caracara population in Florida.

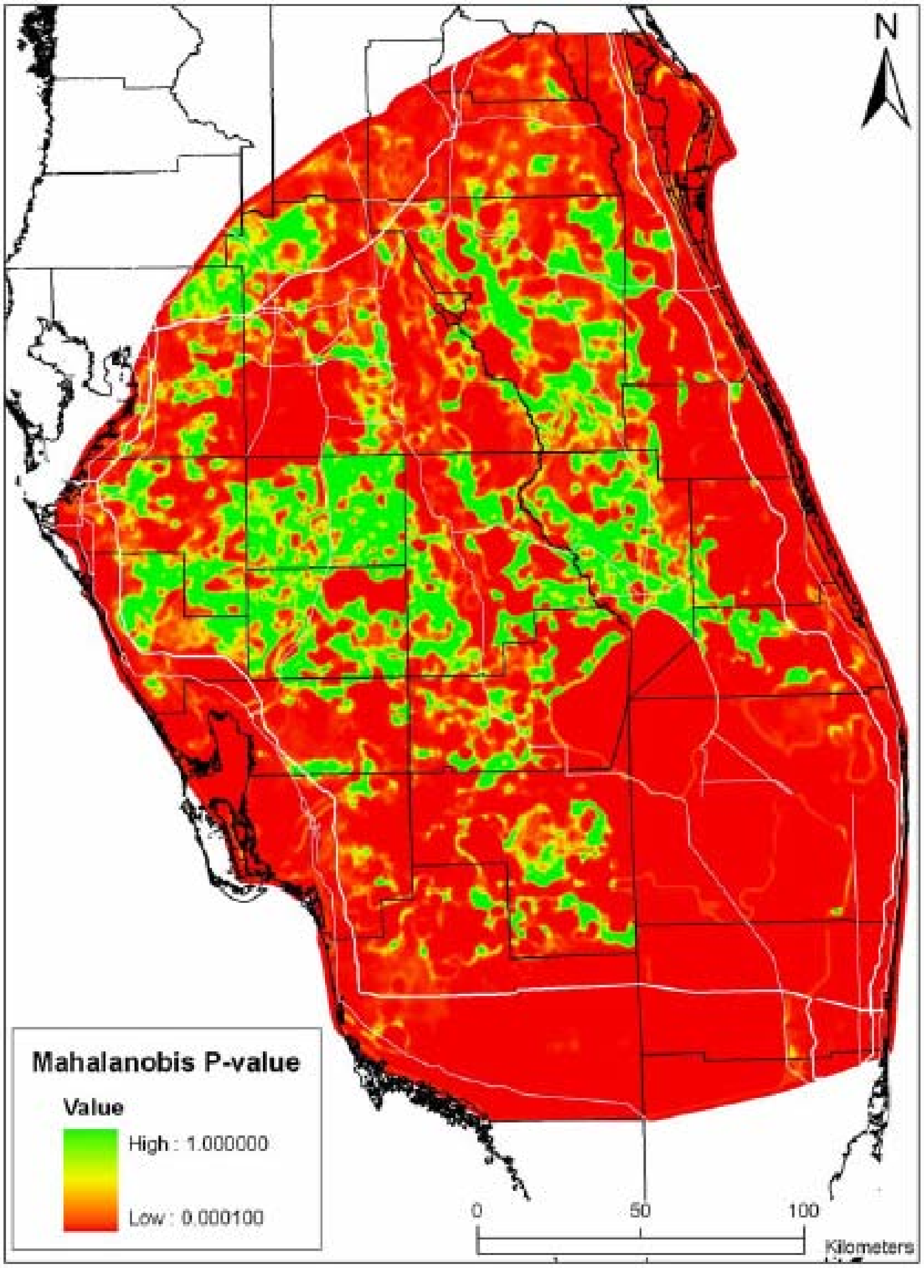

Figure 2. Mahalanobis model of Caracara habitat suitability constructed using home range nest sites (*n*=28). Higher normalized P-values are judged to be more similar to the ideal Caracara habitat based on these home range nest sites.

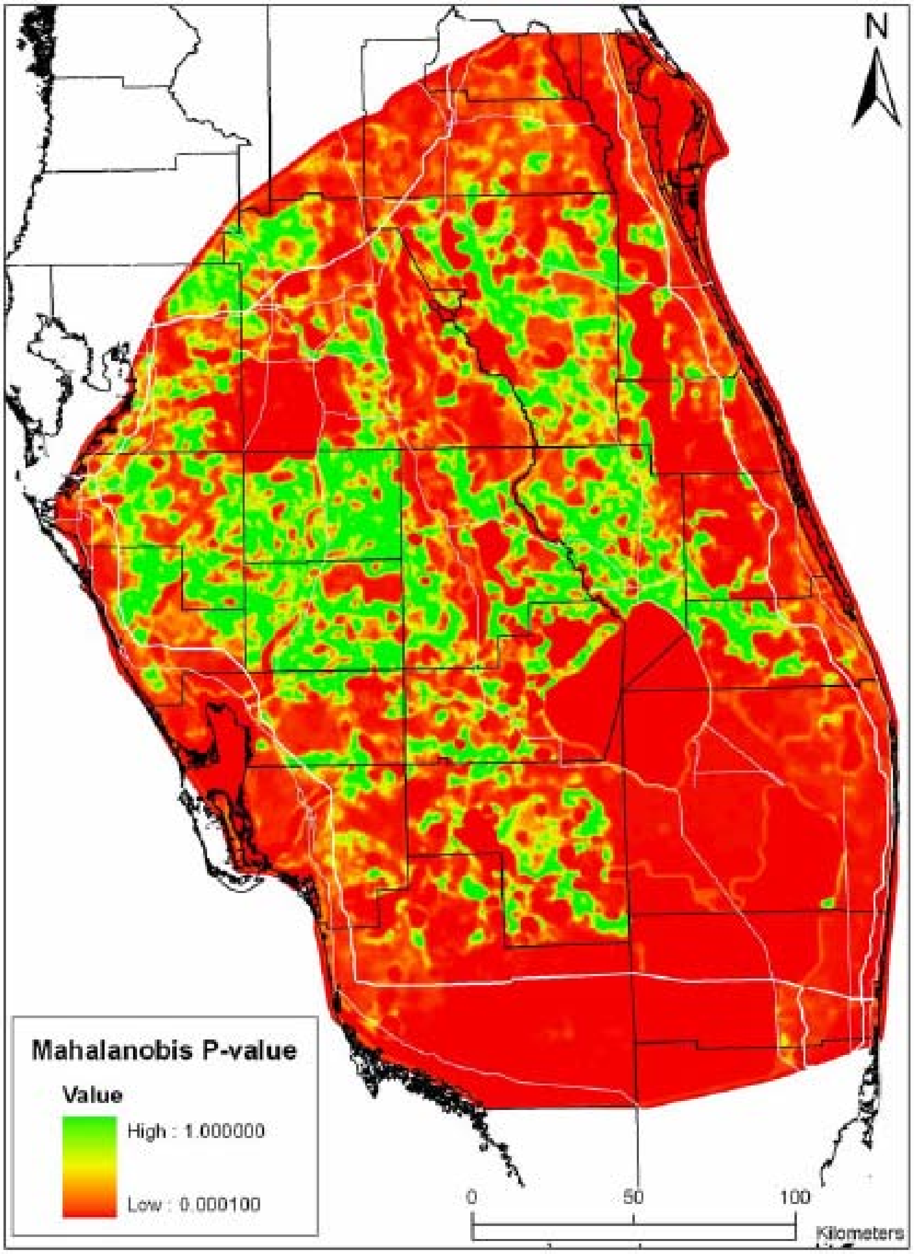

Figure 3. Mahalanobis model of Caracara habitat suitability constructed using center points of home ranges (*n*=28). Higher normalized P-values are judged to be more similar to the ideal Caracara habitat based on these home range nest sites.

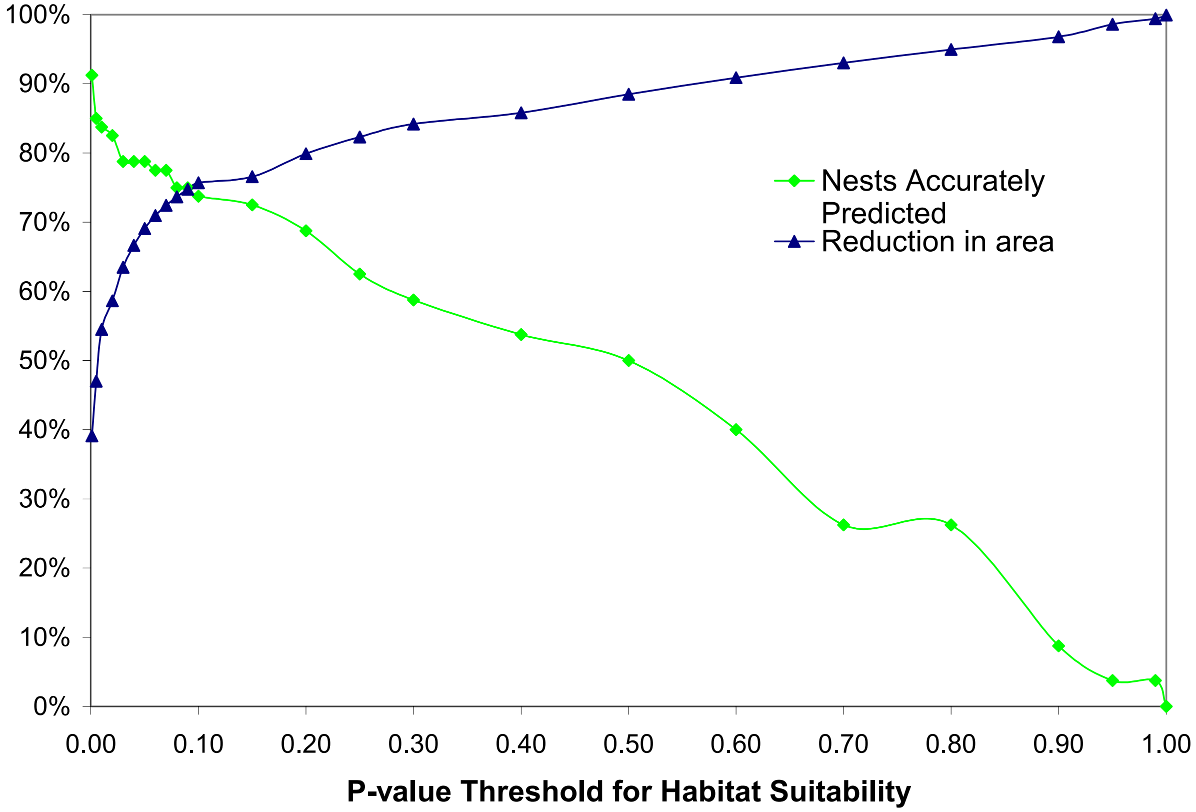

Fig. 4. Results of the Mahalanobis model of Crested Caracara habitat in Florida constructed using actual nest locations within home ranges. Percent reduction of total study area and percent of nests from test data correctly classified as being on suitable habitat are graphed against the corresponding normalized chi-square *P*-value thresholds. A *P* -value of 1 indicates closest to ideal habitat based on known home ranges, while a value of 0 indicates farthest from ideal. Graph indicates trade-off between reduction of total area and accuracy in classifying test data.

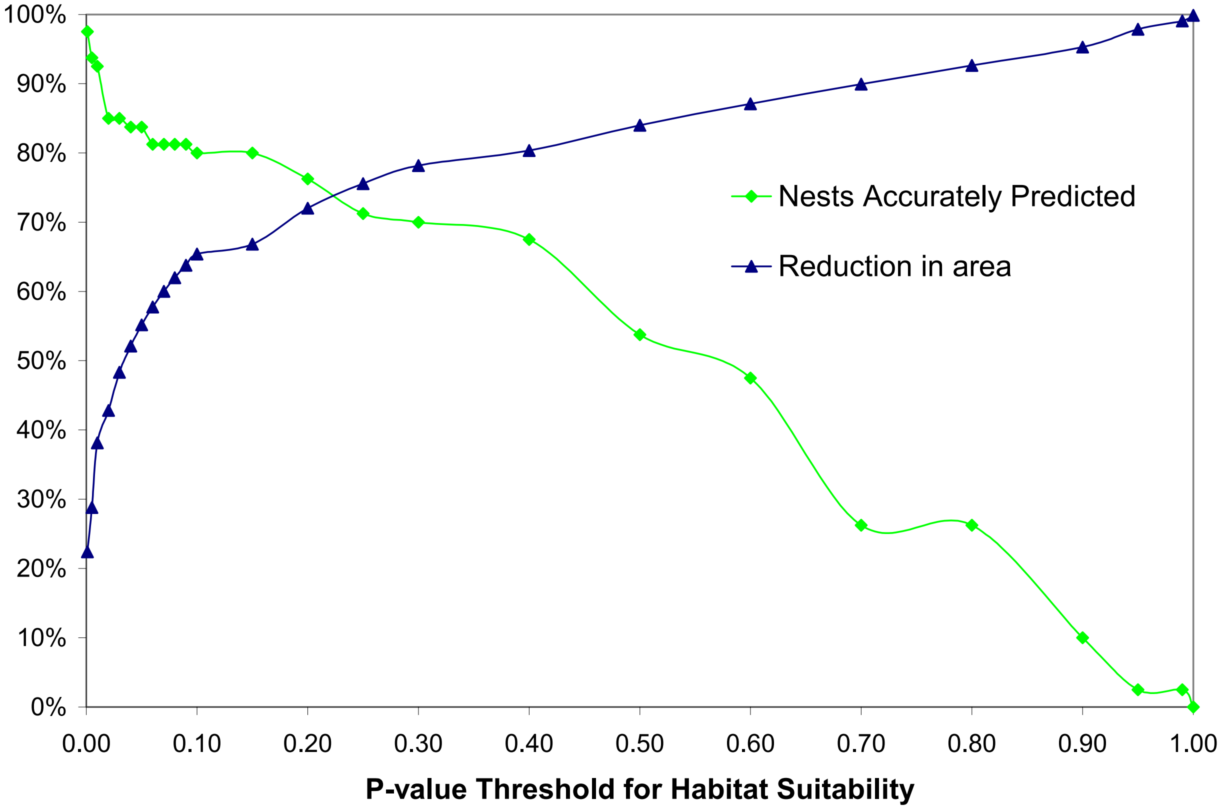

Fig. 5. Results of the Mahalanobis model of Crested Caracara habitat in Florida constructed using the home range center points. Percent reduction of total study area and percent of nests from test data correctly classified as being on suitable habitat are graphed against the corresponding normalized chi-square *P* -value thresholds. A *P* -value of 1 indicates closest to ideal habitat based on known home ranges, while a value of 0 indicates farthest from ideal. Graph indicates trade-off between reduction of total area and accuracy in classifying test data.

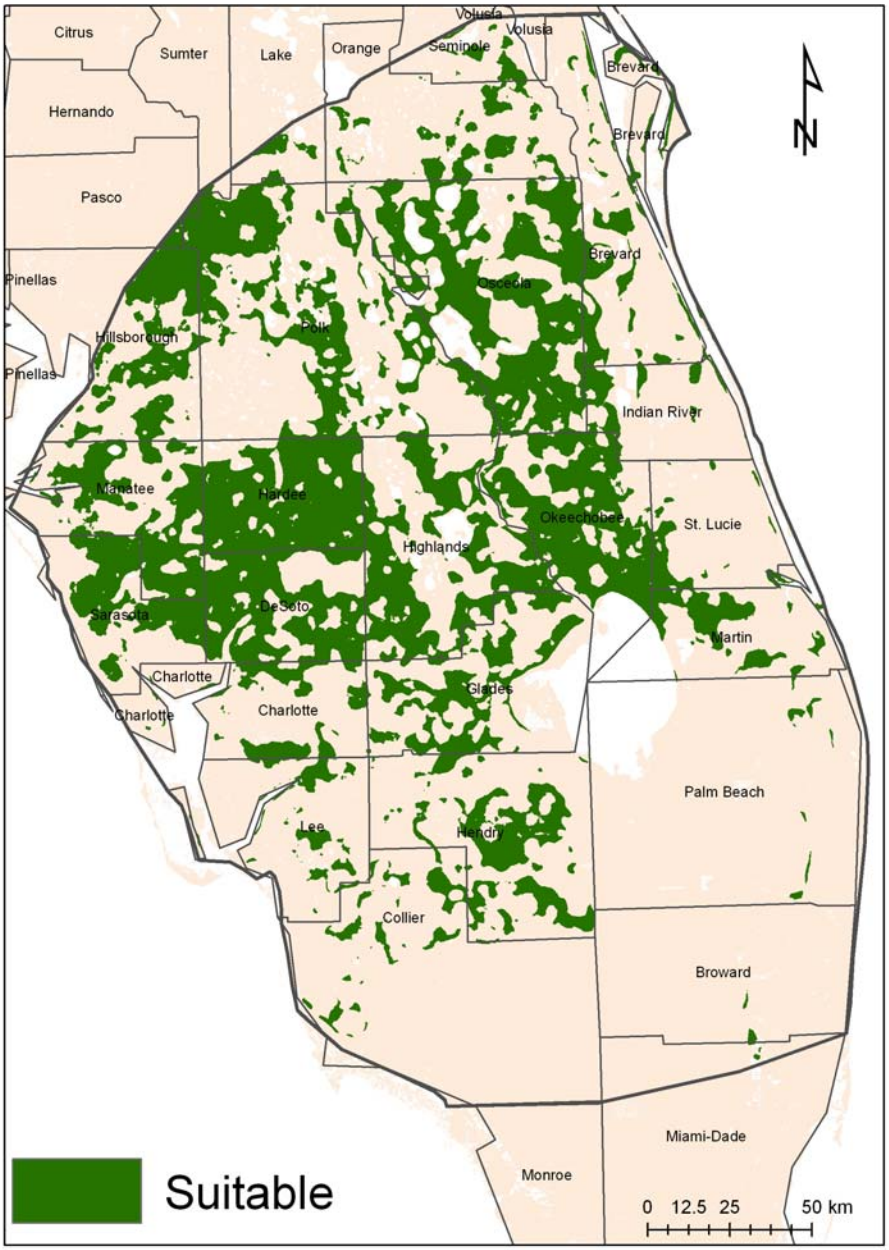

Figure 6. Binary reclassification of the Mahalanobis model of Caracara habitat suitability constructed using home range nest sites. The Mahalanobis model was reclassified using the determined cut-off value (0.09); raster cells with values below the cut-off were reclassified as 0 (predicted unsuitable), and those with values above the cut-off were revalued to 1 (predicted suitable).

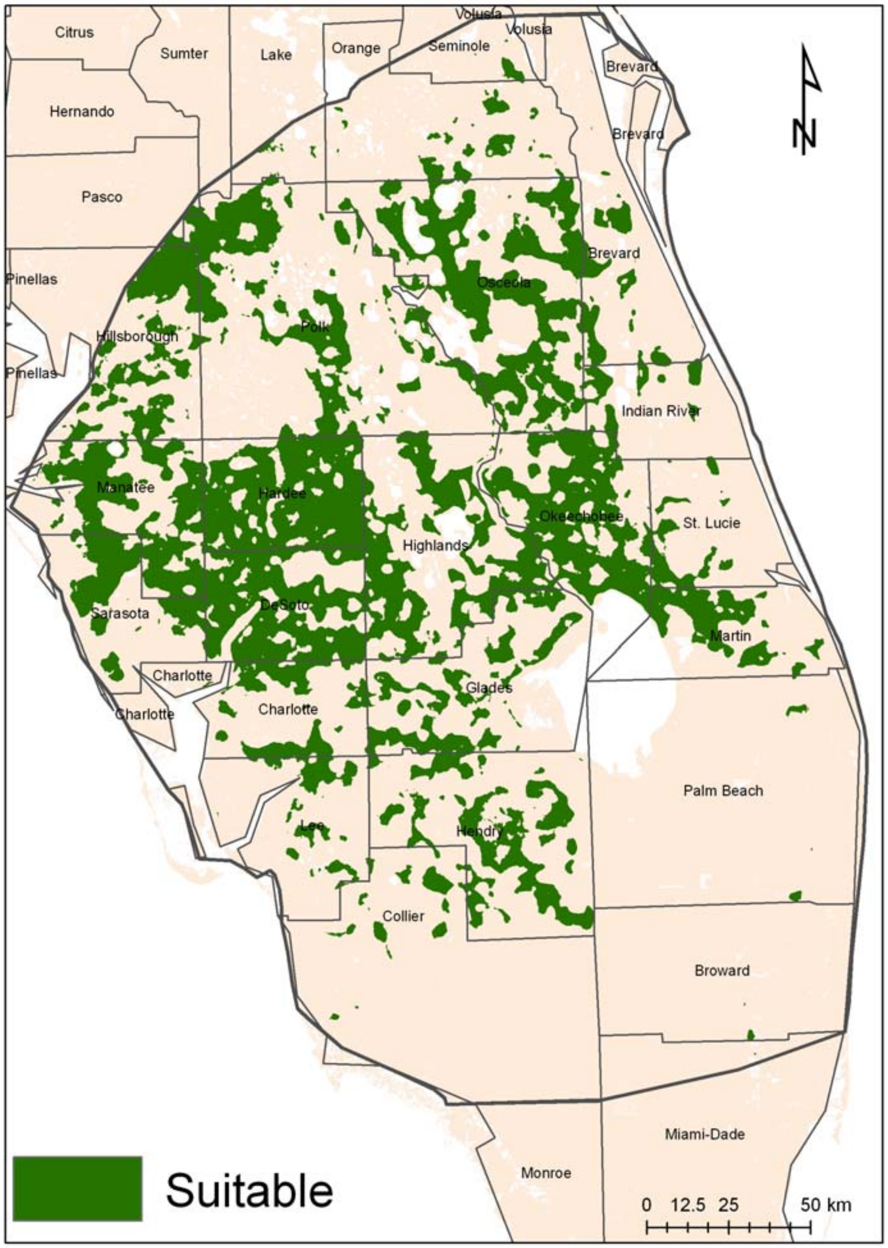

Figure 7. Binary reclassification of the Mahalanobis model of Caracara habitat suitability constructed using the center points of home ranges. The Mahalanobis model was reclassified using the determined cut-off value (0.25); raster cells with values below the cut-off were reclassified as 0 (predicted unsuitable), and those with values above the cut-off were revalued to 1 (predicted suitable).

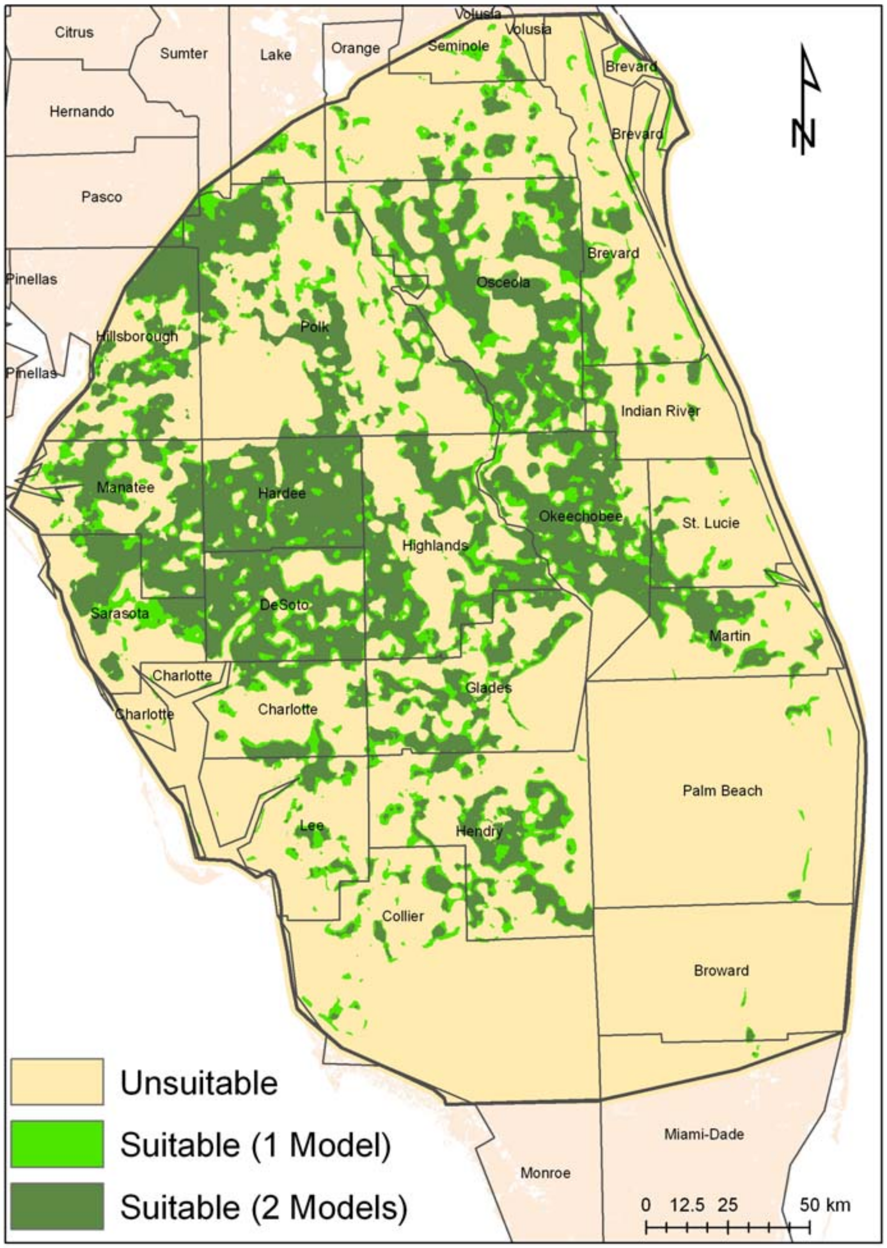

Figure 8. Final predictive habitat model for the Crested Caracara in Florida. This best fit model combines the 2 binary reclassifications of the Mahalanobis models constructed using home range center points and nest locations within each known home range. Total area of predicted suitable habitat of both models (in either 1 model or both) accurately classifies 81.25% of test data (n = 80 nests), while reducing the study area by 72.15%.

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CHAPTER IV

PRIORITIZING HABITAT AND ASSESSING DIFFERENTIAL RISK OF HABITAT LOSS ACROSS THE LANDSCAPE

INTRODUCTION

Understanding the relationships between wildlife and habitat is a core issue in ecology. The relationship is complex, involving simple requirements such as those resources needed to provide breeding, feeding, and shelter, as well as external constraints such as depredation, competition, and availability restrictions (Grinnell 1917; Hutchinson 1957; Svardson 1949). Often these relationships can be hard to unravel, and lead to misunderstandings about habitat use, selection, and quality (Garshelis 2000). For conservation purposes, understanding ecological requirements for a species or population is imperative (Brambilla et al. 2006; Clark et al.1993; Gibson et al. 2004). While understanding the complex interactions of abiotic and biotic factors that impact species distributions is important, we are often under the pressures of crisis management, and do not have the time or resources necessary to fully research these interactions.

With the advent of geographic information systems (GIS) modeling habitat has become a more commonly used and valuable tool for understanding and quantifying habitat requirements. Correlations between specific ecological features and the species of interest can be statistically tested at large scales, and habitat models have been constructed for a variety of species using various statistical techniques such as logistic regression (e.g. Dorrough & Ash 1999; Meyer & Miller 2002; Periera & Itami 1991), habitat suitability indices (e.g. Breininger et al. 1998; Larson et al. 2004; Lauver et al. 2002), and the Mahalanobis Distance (D^2) statistic (Browning et al. 2005; Clark et al. 1993; Corsi et al. 1999; Rotenberry et al. 2006). Habitat models often result in a binary classification of suitable/unsuitable, although in some cases the habitat is prioritized as primary and secondary (Kautz et al. 2006), or as a gradient of suitability (Gibson et al. 2004).

Ultimately, these habitat models are constructed based on where the animals are and what areas have ecological variables most similar to these locations, not necessarily what is optimal. While discussions can be made regarding what constitutes optimal habitat, this is not necessarily useful if habitat is restricted or otherwise unused. After determining which ecological variables constitute habitat for a population and where those areas are on the landscape, further analysis of the distribution and habitat use is also important. Habitat models are based on the ecological features most similar to those areas of identified presence, but animals often occur at different densities across these otherwise similar features based on historical limitations (Anderson et al 2002), behaviorally based aggregations (Dale et al. 2006; de Frutos 2007; Ahlering 2006), or they may be used differently across seasons (Stoner 2001), or life stage (Nijman & van Balen 2003; Sol et al. 2000)

Habitat is rarely used equally across the landscape and abundance and densities often vary widely across a species range with just a few areas showing disproportionately high use (Brown et al. 1995). The idea of a core habitat region based on disproportionate habitat use, and the need to conserve these core regions, is not new (Guyot & Clobert 1997; Hilty & Merenlender 2004; Maehr 1997; Parra 2006; Shkedy & Saltz 2000). All habitat can rarely be conserved and/or managed for a population, so we must assess which areas should be the focus and prioritize conservation efforts accordingly. For a single species, we would ideally define core regions based on the areas of highest fitness, or sources in the case of metapopulations. However, data on site-specific demography are often lacking, and so directly linking habitat areas with fitness is often only an option for the most well-studied species (Davenport et al.

2000; Root 1998). For multiple species prioritization, such as determination of biodiversity hotspots, is often based on occurrence data; where the greatest diversity of species occur (Kiester et al. 1996; Moilanen et al. 2005). Occurrence data have recently been used for single species to define core regions of habitat, sort of within species 'hotspots'. For example, Shkedy and Saltz (2000) used historic opportunistic occurrence data to define core and corridor areas for Nubian Ibex, and Parra (2006) used a kernel density technique on observation data for two species of dolphins to determine core use for each species and their areas of overlap.

In this study, we demonstrate an approach to prioritize habitat for the Crested Caracara (*Caracara cheriway*) in Florida, based on this idea of core habitat use. A predictive habitat model was developed for this species for the range extent of this population in Florida (Chapter III). To refine this model and make the resulting map a truly useful tool for conservation, this map must be prioritized, unless we want to assume that all habitat across the landscape is equal. Based on observations and nest location data, this population is not evenly distributed across the habitat available on the landscape and seems to exhibit a clustering pattern. This indicates that all habitat may not be equally valuable, or at the very least, equally accessible or used across the landscape. We hypothesized that Crested Caracaras in Florida exhibit a significantly clustered distribution across the landscape, and that occurrence data and nesting location would show a consistent pattern of diminishing use as distance increased from some core region of use. We used available occurrence data to test this hypothesis and quantify this population's spatial distribution in Florida based on areas of highest habitat use in order to prioritize habitat across the landscape. This provides a starting point for conservation and management and generates testable questions regarding Caracara habitat relationships in Florida. These questions can be used to inform research, the results of which can then be used to refine the habitat model.

In addition, a demographic model has previously been constructed for this population (Chapter II). After prioritizing habitat, we linked this demographic model to our new prioritized habitat map, and used it to identify the differential impact of habitat loss in various regions on risk of population decline.

METHODS

Study Site

Our study area included much of central peninsular Florida: east to west across the peninsula between both coasts, with the northernmost point in Seminole County, and the southernmost in Miami-Dade County (Figure 1). These boundaries were selected because this area encompasses all documented Caracara observations from several datasets and thus represents the best estimate of the current geographic range of the Caracara population in Florida. These datasets included known nest sites identified through field research (Morrison 1999, Morrison and Humphrey 2001); all radio telemetry locations collected on radio-tagged Caracaras during 1994-2000 (J. Morrison unpublished data); and 2 datasets of Caracara observations: the Florida Fish and Wildlife Conservation Commission’s Nongame Wildlife Program's Wildlife Observation Database and Florida Natural Areas Inventory occurrence records (Anonymous 2006). We wanted to be sure the study area encompassed all known Caracara locations plus an additional 40 km buffer, representing the longest known natal dispersal distance (Nemeth & Morrison 2002), to all locations at the outermost extent of these datasets. The study area totaled approximately 58,980 km^2 in size.

Software

All geographic analyses were conducted using the geographic information system (GIS) software ArcView 9.x (ESRI, Redlands, California, USA). Specific extensions used for analysis are listed in methods. All analyses utilized raster data with 30m cell resolution. Vector data developed during this process were converted to raster data for all analyses. For the spatially explicit demographic model and sensitivity analyses, we used the population modeling software RAMAS GIS (Akçakaya & Root 2002).

Habitat model

The underlying potential habitat model was developed by Barnes et al. (Chapter III). This model was constructed using the Mahalanobis Distance (D^2) Statistic, and land cover and adult Caracara home ranges described in Chapter III. Hereafter, Caracara habitat is defined as those areas identified by this underlying predictive habitat model.

Occurrence data

Observation data layers were used from two sources, the Florida Natural Areas Inventory (FNAI) and the Florida Fish and Wildlife Conservation Commission's Nongame Wildlife Program's Wildlife Observation Database (WILDOBS). Each contained Caracara sightings from a variety of sources including agency researchers, ecologists, and historic sightings. The data from both of these layers were predominately collected between the years of 1978 and 1993. A third layer, including nest locations, was also used. This data layer included the global positioning system (GPS) points of active nest locations collected by Dr. Joan Morrison in 2005 (hereafter identified as NESTS_05). For more detail on metadata for these layers, see Table 1. To test our observation that Caracaras are clustered, we conducted a Nearest Neighbor Analysis in ArcView using Spatial Statistics on each of these three layers. However, the nest locations layer was of primary importance since these points were all of discrete locations collected in the same year.

Defining Core Habitat

To determine if the pattern of habitat use identified a core region of highest density, we used the kernel density function in the Spatial Analyst extension in ArcView 9.x. Using the 3 data layers of occurrence data described above, and a 5 km radius, we calculated a kernel density layer for each. This radius spans approximately 3 Caracara home ranges of average size. We used a cut-off of 50% kernel density to define high density areas for each layer. A minimum convex polygon (MCP) was then drawn to encompass ≥95% of these high density areas. This polygon was defined as the core region. Buffers were drawn around the core at a distance of 30 km, until the entire study area was regionally defined as either within core or within a sequential buffer of 30, 60, 90, 120, 150, or 180 km from core. Buffer distance was chosen to encompass the average natal dispersal distance observed in females (Nemeth & Morrison 2002). This buffer layer was then combined with the habitat model, so that each cell defined as habitat was also defined as belonging in either the core or a subsequent buffer. Hereafter, these are identified as regions named core, 30km, 60km, 90km, 120km, 150km, or 180km.

Determining a relationship

Using the point intersect tool in Hawth's Tools (Beyer 2004), we classified each point in all three occurrence data layers according to region. Density of occurrences was calculated for all three layers, separately, to standardize for differences in the area of each region. We then calculated the change in density of observations from each region to the next. This change in density of occurrence was then used as a proxy for change in carrying capacity (K) of females across the landscape.

Linking the Map to the Demographic model

The baseline population model previously developed (Chapter II) was used as a foundation for these analyses. This demographic model was a 3-stage, females-only model. To determine if habitat loss in different regions differentially impact risk, we modeled an absolute amount of loss of habitat in each region using a reduction in K as a proxy for habitat loss. A habitat suitability function was calculated based on the change in density across regions as described above, which was used to calculate differences in K across regions, and the decrease in K with specific amounts or rates of habitat loss. We used an absolute amount of 120 km^2 as a one time reduction in K in each region, and assessed impact on risk and abundance of females over time. This absolute amount is the approximate size of 10 Caracara home ranges of average size. We then modeled a decrease of 120 km^2 every 10 years to assess the impact on risk of habitat loss in each region over time. Following an initial loss at year 5, habitat was again reduced at year 15, 25, 35, and 45 in each region in separate simulations. The final scenario was a one time loss of 600 km^2 in each region. This final scenario allowed us to compare difference in risk between losing 600 km^2 iteratively across time (as in the 2nd scenario) and losing that same amount in one event.

In addition to habitat loss, we also assessed K on managed lands. Using the Florida Managed Areas Inventory GIS data layer (Anonymous, 2007), we determined how much of each region was currently designated as a managed area, used the habitat suitability index to estimate the K that public lands in each region could support, and assessed risk if all habitat on private lands was lost, leaving only Caracaras on public lands.

For all scenarios, we report two types of results: a trajectory summary which shows the mean abundance of females over time; and interval percent decline, which shows the probability of a percent decline below initial abundance at any interval in the model duration. All models were run over a 50 year time course for 1000 replications. Initial abundance was set at carrying capacity (500 females) for all scenarios. This is a conservative best estimate of current abundance in Florida, and the population was assumed to be at or near carrying capacity (Morrison, pers.com.).

RESULTS

Occurrence data

Nearest Neighbor Analysis confirmed that for each occurrence data layer, occurrences are significantly clustered based on Z Score test: FNAI (z-score = -5.4, $P<0.01$), WILDOBS (z-score = -20.04, $P<0.01$), NESTS_05 (z-score = -4.73, $P<0.01$).

Defining Core Habitat

High kernel density areas for all three occurrence data layers converged in a central area northwest of Lake Okeechobee (Figure 1). The polygon drawn to encompass 95% of this high density area, hereafter identified as core, contained 1,655.36 km^2, of which 52.22% was identified as suitable by the habitat model (Table 2). To include the entire study area, 6 buffers were necessary. This resulted in 7 total regions: core and 30, 60, 90, 120, 150, and 180 km buffers; distance was from core outer edge to outer edge of buffer (Figure 2). Core had the highest percent of its region identified as suitable, closely followed by the 30 km region, and diminishing as you moved farther from the core (Table 2).

Determining a relationship

The majority of occurrences in all 3 layers were located in the core, 30km and 60 km regions (Table 3). When the occurrence data for each layer was standardized for total region area by converting these values to density of occurrence/km^2, a clear pattern of diminishing occurrences can be observed as you move from the core to the outer regions (Figure 3 & Table 4). The change in density as you move from one region to the next was calculated for all 3 layers separately, and averaged across all 3 for each region (Table 5). The average value of a 69% decrease from one region to the next was chosen as our proxy for change in carrying capacity across the study area. This overall average value was chosen instead of using more specific averages for each region because the precision of this value should not be overstated. Each region was assigned a suitability value based on this decrease in occurrence density. These values were for each 30m cell in our habitat model. Core was assigned a suitability value of 1, the 30km region suitability value was calculated as 1* 0.31 (value of previous region reduced by 69%), 60 km region as 0.31^2 (value of previous region (0.31) reduced by 69%), 90km as 0.31^3, and so forth (Table 6). We translated this into a proxy of K by adding the total suitability value of all cells identified as habitat by our underlying model, and dividing this total value by a population K of 500 females. This resulted in a constant of 0.00017213, which is the average calculated density of females per cell. This constant was then multiplied by the suitability value of each 30m cell (defined by the region the cell is in) to obtain an expected density of females for that cell. This was calculated to determine an estimate of K for each region (Table 6).

Linking the Map to the Demographic model

When an absolute amount of habitat (120 km^2) was removed from each region, the greatest decrease in abundance of females and the greatest increase in risk (i.e. interval percent decline) was removal in the core region, followed by the 30 km region; reducing habitat in subsequent regions differed little in risk from baseline models with no loss of habitat (Figures 4 & 5). The probability of a 15% percent decline doubled from 0.42 when no habitat loss was simulated, to 0.84 when habitat loss was focused in the core (Kolmogorov-Smirnov Test, x=15.4, p<0.0001).

Iterative reductions of habitat over time showed similar results, with the highest negative impact to both abundance of females and risk of decline demonstrated when habitat was lost in the core region. Abundance of females was reduced from a mean of 490 females in the 'no habitat loss' scenario to mean of less than 380 at the end of the 50 year simulation (Figure 6). Similarly, the probability of a 25% decline below initial abundance increased from 0.02 in the 'no habitat loss' scenarios to 0.92 when habitat was reduced in the core region, but only 0.07 when habitat loss was focused in the 30km region (Figure 7).

This same pattern of highest impact from habitat loss in the core region followed in the next scenario when a one time habitat loss of 600 km2 was simulated (Figures 8 & 9). Even more interesting, though, was that risk increased significantly when habitat was lost in one large amount of 600 km2, compared to losing the same amount divided in 5 equal intervals over time (as in the previous scenario), even though abundance of females at the end of both scenarios was the same (Figures 10). The probability of a 32% percent decline increased from 0.27 when habitat loss occurred over time in the core region, to 0.88 when habitat loss occurred in one event (Kolmogorov-Smirnov Test, x=31.8, p<0.0001;Figure 11).

We estimated that only 15% of the core region was designated as a managed area by the Florida Natural Areas Inventory, and less than 12% of the 30 km region (Table 10) . In all, only 14% of all area identified as suitable by the underlying habitat model was under some level of management (Figure 12). When habitat was reduced to only those lands currently under management, there was a dramatic decline of abundance and increase in risk. Average abundance of females was reduced from 490 to less than 60, and risk of a 90% decline was increased from a probability of 0 to 0.94 (Figures 13 & 14).

DISCUSSION

The underlying habitat map that we developed successfully identified habitat for the Crested Caracara in Florida (Chapter III). Ideally, we would then seek to protect all of this area for the Caracara, and manage it accordingly. Obviously, this is unrealistic. Florida is currently the most densely human populated state in the U.S., and rates of population and the resulting development show no signs of declining (Florida Fish & Wildlife Conservation Commission 2005). In order to increase the utility of the habitat map for conservation efforts, we sought to determine if habitat was being used differentially across the landscape, and prioritize accordingly.

Based on currently available data, our neighborhood analysis showed that Crested Caracaras were indeed exhibiting a clustered distribution, and our kernel density analyses showed that the core of their habitat use seemed to focus in a single primary region of their range in Florida. Occurrence data declined at a high rate from one region to the next. Linking this prioritized map to our population model showed that habitat loss impacts risk of decline differently, depending on where that loss was focused. More specifically, habitat loss in the core region increased risk significantly compared to similar rates of loss in any other region Although historic distribution maps for the Caracara in Florida are not available, descriptive accounts from the early half of the century support that they have a core region of habitat (Howell 1932; Nicholson 1929). However, we do not understand why occurrence data suggest that habitat use is so highly clustered in certain regions, while our predictive habitat model showed that suitable habitat was distributed across their range into areas that seem to be relatively unused.

This clustered distribution could occur for a variety of reasons. First, occurrence data could have some level of bias in certain areas. Although this is a possibility, both the Wildlife Observation Database and the Florida Natural Areas Inventory are statewide databases, so it is unclear why there would be a higher report rate in some areas over others. Secondly, this could be an artifact of historic distribution. Caracaras were historically linked to dry prairie, and the largest of these areas were historically located just north and west of Lake Okeechobee (U.S. Fish & Wildlife Service 1999). Florida's dry prairie region is listed as globally imperiled, much of it has now been converted to improved pasture; Caracaras are now commonly associated with this land cover/land use feature (U.S. Fish & Wildlife Service 1999). Third, this could be related to behavioral cues. In some territorial species, especially birds, offspring settle in unoccupied territories near their natal range. In some cases, this has been shown to be a function of conspecific attraction – birds settle where they observe or hear the calls of other birds of their own species (Laysan Albatross -- Podolsky 1990; Black-capped Vireo --Ward & Schlossberg 2004). Another hypothesis for clustering distributions in birds is that they are utilizing environmental cues that are most like those from the area in which they were raised (Stamps & Swaisgood 2007). Finally, this could be due to specific local characteristics not picked up by the underlying predictive habitat model. The underlying habitat model was based on landscape features, and was insensitive to local features such as structure, which would be important for nesting. The insensitivity to local characteristics and other caveats to the underlying model are discussed in Chapter III.

Of primary importance for conservation efforts and the use of this prioritized regional model, is verifying this unequal habitat use with field surveys. This will truly determine the efficacy of our prioritization framework and risk assessment. This can be done with a relatively rapid assessment approach, using agency staff and other researchers already in the field working on other projects to simply log observations with GPS points and a few basic pieces of information (e.g. number of individuals, date, and (if possible) description of plumage color to determine age). If occurrence data shows a significant difference in densities from our calculations, this framework can be used to recalculate and reprioritize relatively easily.

Secondly, and especially for mitigation efforts, determining why they are clustering is the next step for research. Conspecific attraction is likely, as this a long observed and supported hypothesis for colonial bird species (Jeffries & Brunton 2001; Kress 1997; Podolsky 1990), but more recently, this has also been found in a territorial songbird (Ward & Schlossberg 2004), and some species of raptors (de Frutos 2007; Sergio 2005). This clustering behavior based on conspecific attraction may have a direct impact on fitness; Fletcher (2006) used an individual based modeling approach to assess impact of conspecific attraction on fitness, and found that when habitat quality cannot be directly assessed, conspecific attraction has a positive impact on fitness. Fletcher's work supports the notion that local ecological characteristics and conspecific attraction may be correlated, i.e., presence of conspecifics as an indirect indicator of habitat suitability.

Without understanding why they are clustering, we do not know if areas are interchangeable. For example, based on our prioritization, it would be tempting to conclude that destruction of a parcel of land in the core region could be mitigated by restoring habitat 3-4 times the size of that parcel in the 30km region. If local environmental factors are different, this may not be effective. For example, Caracaras could be in certain areas at lower densities because necessary local scale habitat features are missing. If clustering is due to conspecific attraction, Caracaras may simply not move to the new area if others are not already present. Clearly, additional research is necessary.

We do not wish to undermine the utility of this approach, however. Brown et al. (1995) used breeding bird survey data and additional niche simulations to look at patterns of species distribution based on occurrence, and found that density is highly variable for numerous species across their range. They emphasize the importance of using information on abundance, and not just presence and/or absence data to define habitat and make sound management decisions. The work presented in this chapter compliments our earlier development of a predictive habitat model based on presence (Chapter III) by attempting to quantify this differential distribution pattern across the landscape, thus incorporating both of these aspects. We have successfully demonstrated how using occurrence data to quantify patterns of habitat use across the landscape can be useful in generating testable hypotheses and guide research. Using this framework of developing regions with different levels of suitability (by which, we make no inference of quality), we have shown through a variety of simulations that habitat loss likely has different degrees of impact on the population's risk of decline depending on where the loss occurs. The scale we chose (i.e. 30 km regions) is appropriate for this highly vagile species; however, the scale of this method can be increased or decreased for use on other species or systems. With testing and refinement, this method can be used to assess the relative impact of habitat destruction in certain areas compared to others, focus conservation efforts, and also show us where gaps in our understanding of this population occur.

Table 1. Metadata for the GIS data layers used to define core habitat for the Crested Caracara in Florida.

Data Layer	Metadata
All_Nests2005.shp	This layer was obtained from Dr. Joan Morrison, and includes locations of all nests currently observed in her research efforts as of 2005. (Morrison, unpublished data).
Wildobs.shp	Florida Fish and Wildlife Conservation Commission's Nongame Wildlife Program's Wildlife Observation Database. Observations for the Caracara were isolated from this layer. Caracara occurrences included 308 observations from Dr James Layne and employees of Florida Fish and Wildlife Conservation Commission, recorded between 1978 and 1993.
Fleo.shp	Florida Natural Areas Inventory Occurrence Records (Anonymous, 2006) Available at http://www.fnai.org/index.cfm Caracara observations were isolated from this layer. Carcara occurrences included 214 observations from 1978-1997, and included unpublished records from Dr. James Layne and employees of Florida Fish and Wildlife Conservation Commission
FLMA.shp	The GIS layer includes boundaries for more than 1,600 federal, state, local, and private managed areas, all provided directly by the managing agencies. National parks, state forests, wildlife management areas, local and private preserves are examples of the managed areas included. The managed areas shapefile is updated quarterly. Last update March 2007. Available at http://www.fnai.org/gisdata.cfm

Table 2. Total amount of area (in km^2), total area identified as suitable (in km^2), and percent of area identified as suitable within each region.

	# of cells in region	Region Area (km2)	Suitable habitat in region (km2)	Percent of Region identified as suitable
Core	1,839,291	1,655.36	864.4311	52.22%
w/in 30 km	8,999,583	8,099.62	3678.5061	45.42%
w/in 60 km	15,278,475	13,750.63	4955.7015	36.04%
w/in 90 km	19040430	17,136.39	3471.597	20.26%
w/in 120 km	15668882	14,101.99	2917.7037	20.69%
w/in 150 km	6300419	5,670.38	998.2071	17.60%
w/in 180 km	286542	257.89	6.3387	2.46%

Table 3. Occurrences of Crested Caracaras in Florida from three data layers (Florida Fish and Wildlife Conservation Commission's Nongame Wildlife Program's Wildlife Observation Database (WILDOBS), active nest locations as of 2005 (Nests_05), and Florida Natural Area Inventory database (FNAI)) within each region.

	Wildobs	Nests_05	FNAI	Total
Core	124	33	51	208
w/in 30 km	124	50	76	250
w/in 60 km	47	18	57	122
w/in 90 km	10	4	22	36
w/in 120 km	3	2	8	13
w/in 150 km	0	0	0	0
w/in 180 km	0	0	0	0
Total	308	107	214	629

Table 4. Density (per km^2) of Crested Caracara occurrences in Florida from three data layers (Florida Fish and Wildlife Conservation Commission's Nongame Wildlife Program's Wildlife Observation Database (WILDOBS), active nest locations as of 2005 (Nests_05), and Florida Natural Area Inventory database (FNAI)) within each region.

	Wildobs	Nests_05	FNAI	Total
Core	0.07491	0.01994	0.03081	0.12565
w/in 30 km	0.01531	0.00617	0.00938	0.03087
w/in 60 km	0.00342	0.00131	0.00415	0.00887
w/in 90 km	0.00058	0.00023	0.00128	0.00210
w/in 120 km	0.00021	0.00014	0.00057	0.00092
w/in 150 km	No Data	No Data	No Data	No Data
w/in 180 km	No Data	No Data	No Data	No Data

Table 5. Percent decrease in occurrence density Crested Caracara occurrences in Florida from three data layers (Florida Fish and Wildlife Conservation Commission's Nongame Wildlife Program's Wildlife Observation Database (WILDOBS), active nest locations as of 2005 (Nests_05), and Florida Natural Area Inventory database (FNAI) as you move from one region to the next.

	Wildobs	Nests_05	FNAI	Avg. across all layers
Core				
w/in 30 km	0.7956	0.6903	0.6954	0.7271
w/in 60 km	0.7767	0.7879	0.5582	0.7076
w/in 90 km	0.8293	0.8217	0.6903	0.7804
w/in 120 km	0.6354	0.3924	0.5581	0.5287
w/in 150 km	No Data	No Data	No Data	No Data
w/in 180 km	No Data	No Data	No Data	No Data
Avg	0.7593	0.6731	0.6255	0.6860
SD	0.0854	0.1952	0.0778	0.1093

Table 6. The suitability value for each region, based on change in occurrence density from one region to the next, multiplied by the number of cells identified as suitable in the underlying habitat model within each region. Calculated carrying capacity (K) of female Crested Caracaras in Florida is shown, based on this calculation, for each region.

	Suitability Value	# of Suitable Cells	Suitability * # of Cells	k
Core	1.0000	960479	960479.00	165.331
w/in 30 km	0.3100	4087229	1267040.99	218.101
w/in 60 km	0.0961	5506335	529158.79	91.086
w/in 90 km	0.0298	3857330	114913.72	19.781
w/in 120 km	0.0092	3241893	29939.56	5.154
w/in 150 km	0.0029	1109119	3175.31	0.547
w/in 180 km	0.0009	7043	6.25	0.001
		Total	2904713.63	500

Table 7. Percent of areas in each region of the study area in Florida designated as managed areas by the Florida Natural Areas Inventory.

	Percent of region currently designated as a managed area
Core	15.04%
w/in 30 km	11.38%
w/in 60 km	10.74%
w/in 90 km	14.79%
w/in 120 km	10.47%
w/in 150 km	35.98%
w/in 180 km	20.66%

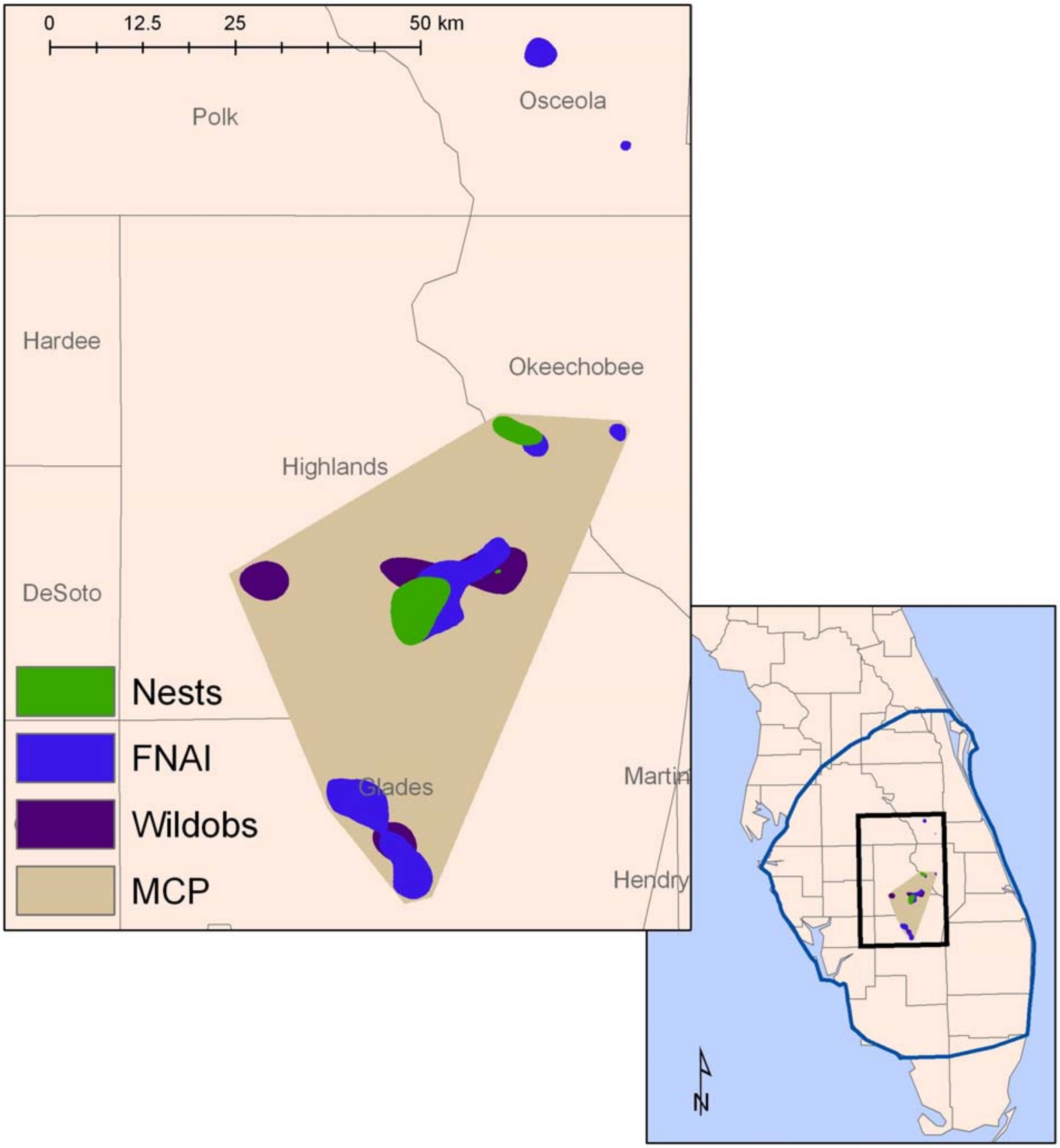

Figure 1. Shows areas within 50% kernel density in each of three occurrence data layers: Nests_05 (Morrison 2005, unpublished data), Florida Natural Areas Inventory database (FNAI), and Florida Fish and Wildlife Conservation Commission's Nongame Wildlife Program's Wildlife Observation Database (WILDOBS). The minimum convex polygon (MCP) drawn to encompass the majority (>95%) of these high density areas is also shown. The study area is outlined in blue; this area represents the best estimate of the current geographic range of the Caracara population in Florida.

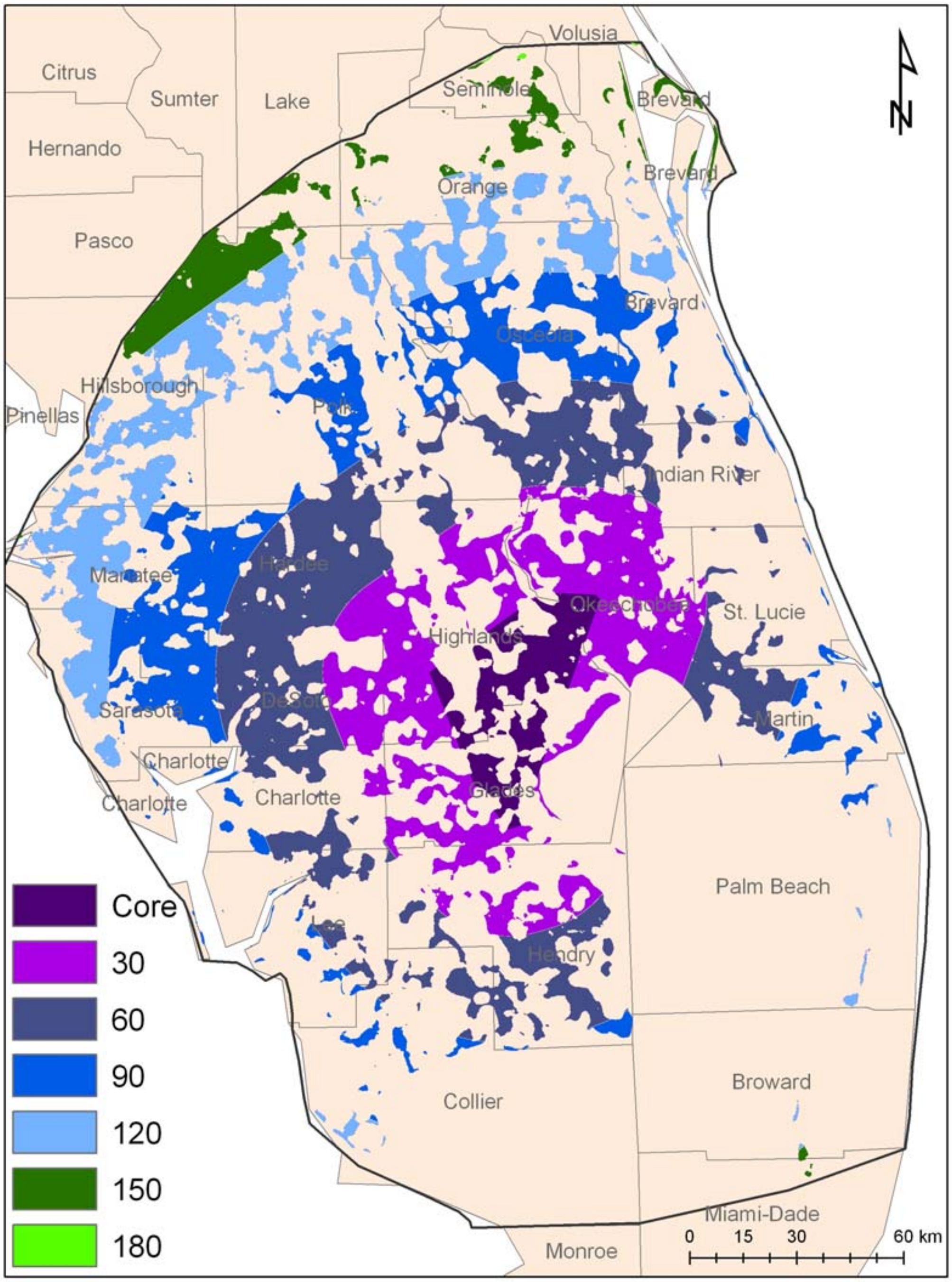

Figure 2. Suitable habitat for the Crested Caracara in Florida, classified by region as either core habitat or distance within successive 30 km buffers of the core. Outer perimeter of study area is outlined.

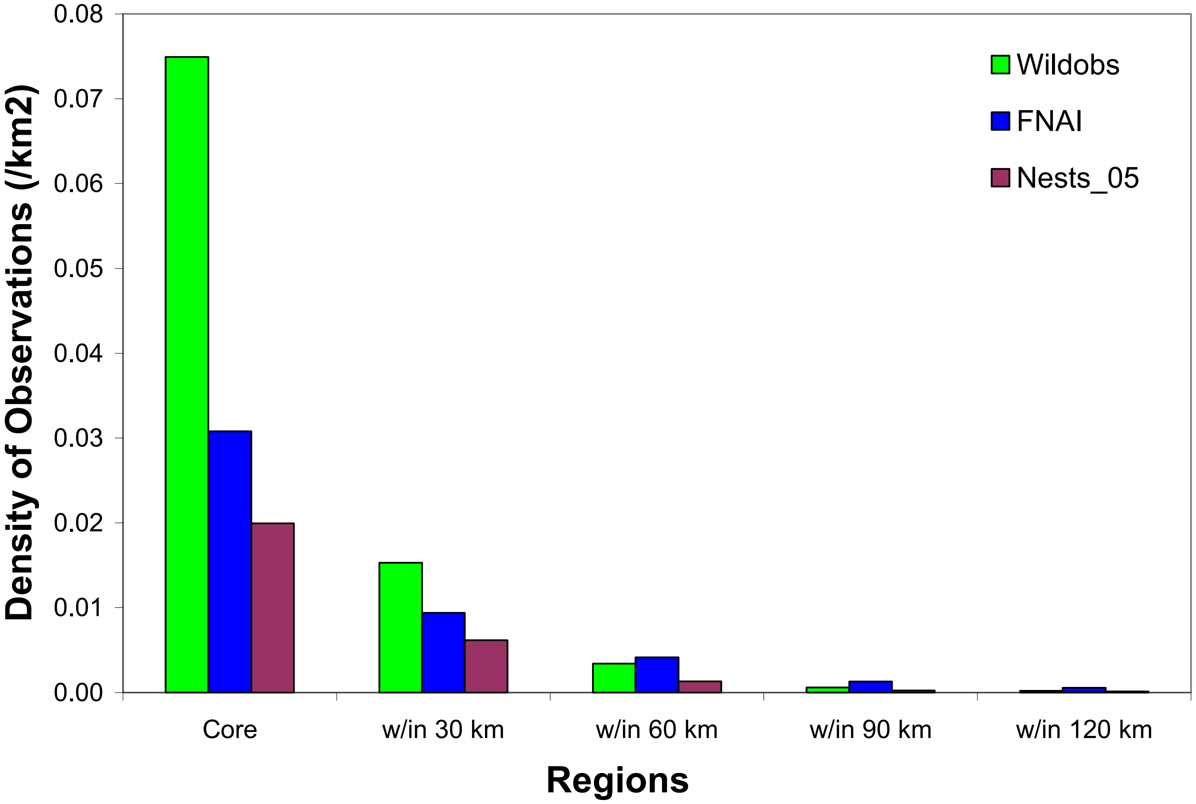

Figure 3. Density of observations (per km^2) of the Crested Caracara in Florida using three occurrence data layers: nest locations (NESTS_05), Florida Natural Areas Inventory database (FNAI), and Florida Fish and Wildlife Conservation Commission's Nongame Wildlife Program's Wildlife Observation Database (WILDOBS).

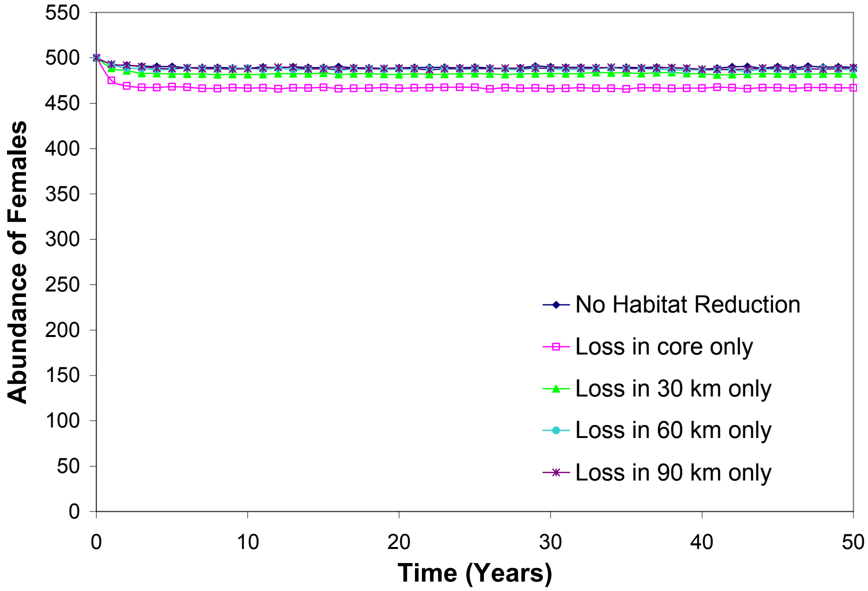

Figure 4. Mean final abundance of females over the 50 year simulation comparing baseline model with no habitat reduction and reducing habitat by 120 km^2 in one region in each model (i.e., core, 30km buffer, etc.).

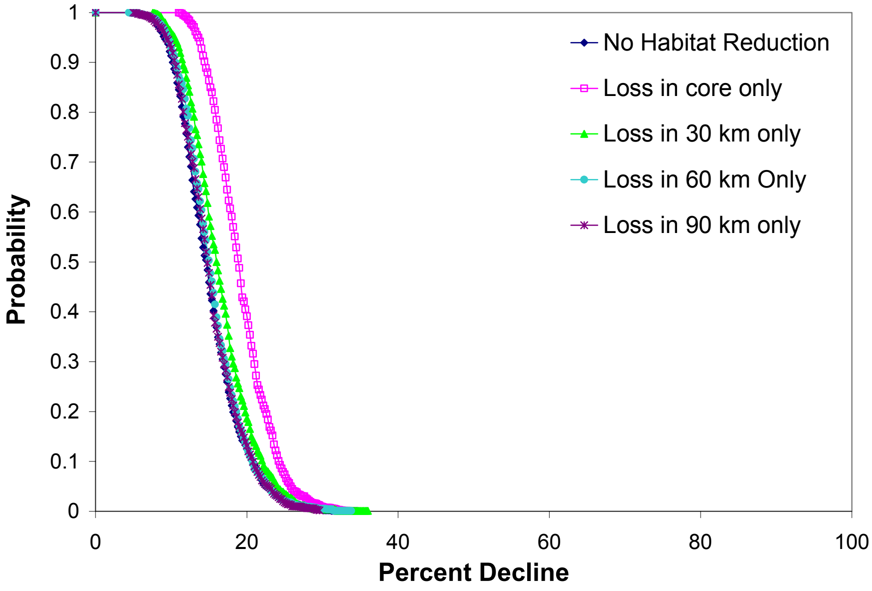

Figure 5. Probability of a percent decline in abundance over the 50 year simulation comparing baseline model and reducing habitat by 120 km^2 in one region in each model (i.e., core, 30km buffer, etc.).

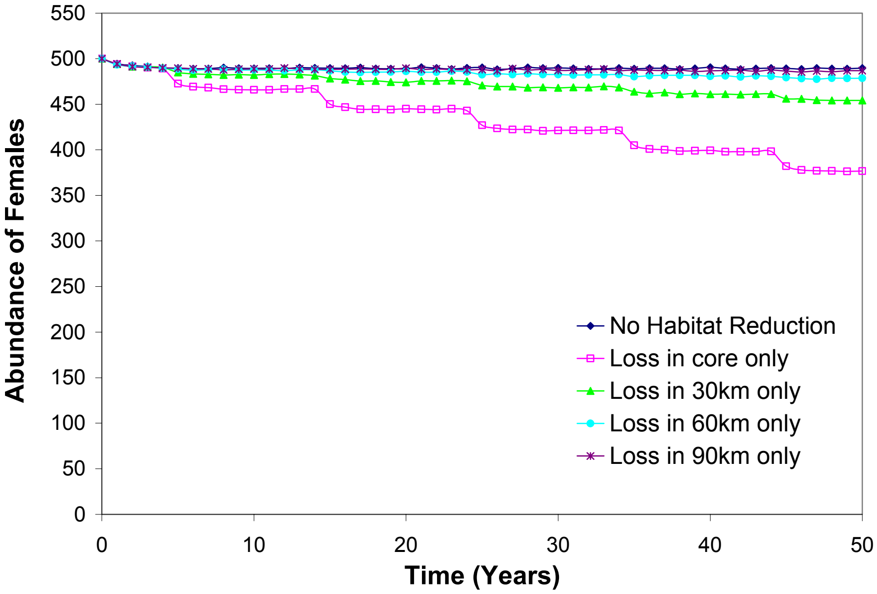

Figure 6. Mean final abundance of females over the 50 year simulation comparing baseline model with no habitat reduction and reducing habitat by 120 km^2 in one region in each model (i.e., core, 30km buffer, etc.) every 10 years, beginning at year 5.

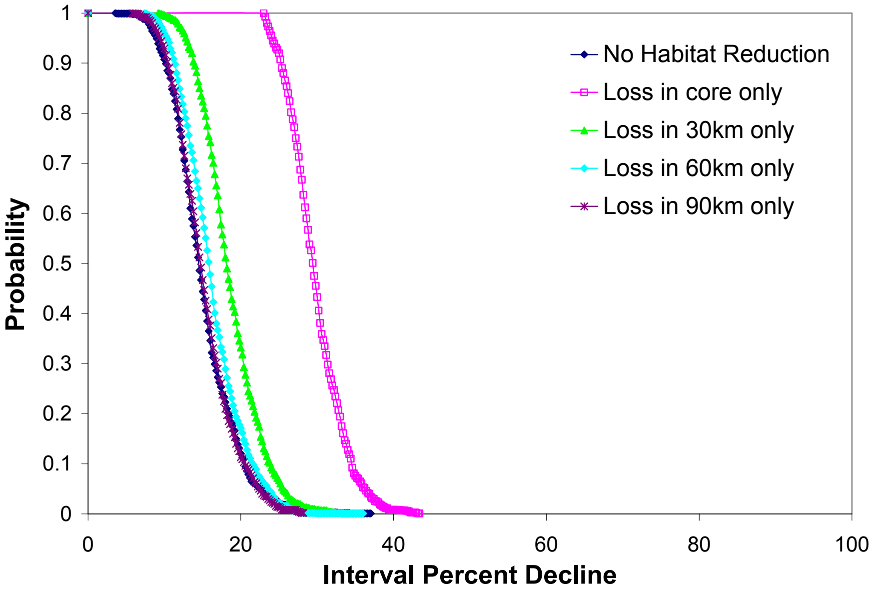

Figure 7. Probability of a percent decline in abundance over the 50 year simulation comparing baseline model with no habitat reduction and reducing habitat by 120 km^2 in one region (i.e., core, 30km buffer, etc.) in each model every 10 years, beginning at year 5.

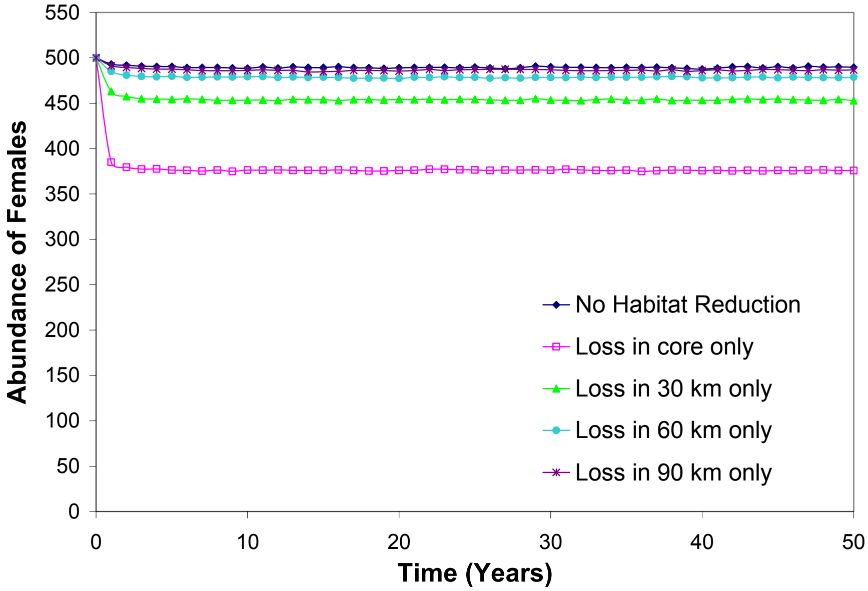

Figure 8. Mean final abundance of females over the 50 year simulation comparing baseline model with no habitat reduction and reducing habitat by 600 km^2 in one region in each model (i.e., core, 30km buffer, etc.).

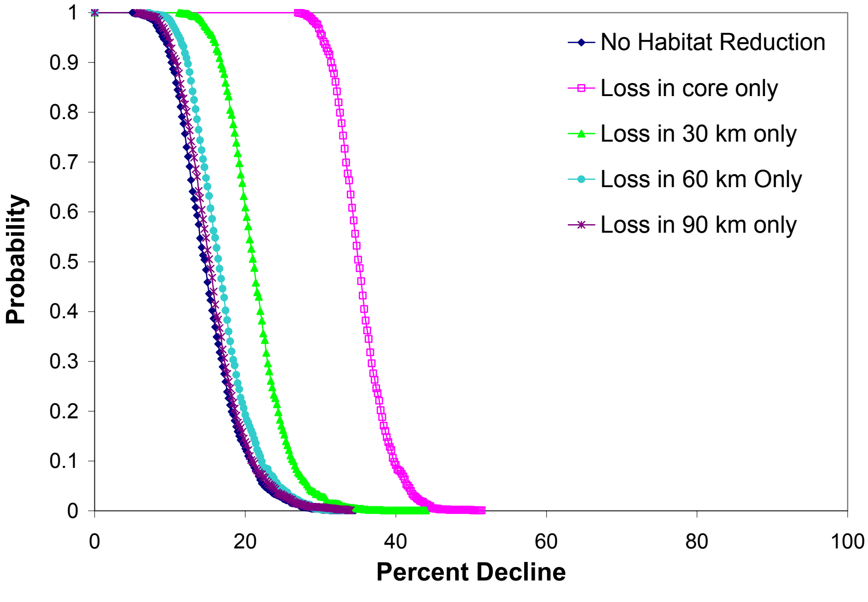

Figure 9. Probability of a percent decline in abundance over the 50 year simulation comparing baseline model with no habitat reduction and reducing habitat by 600 km^2 in one region in each model (i.e., core, 30km buffer, etc.).

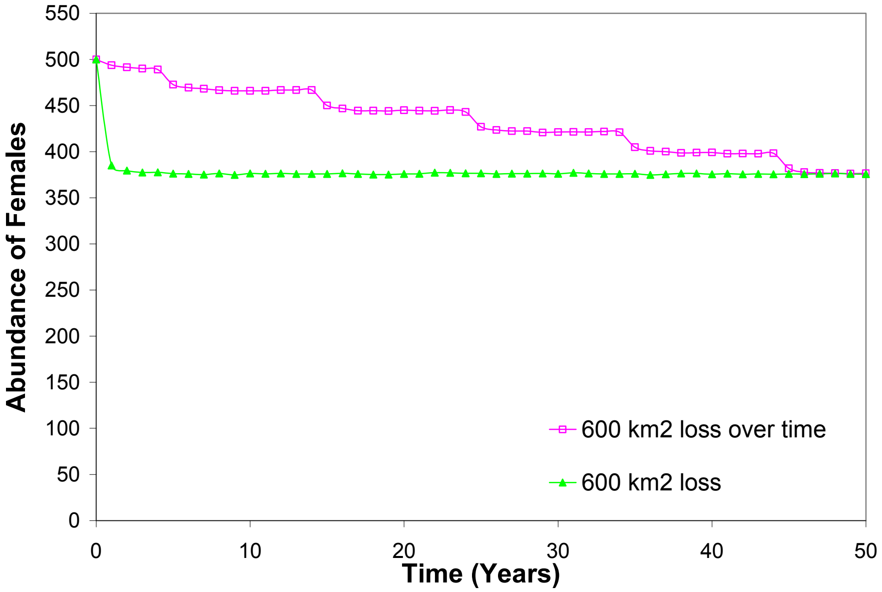

Figure 10. Mean final abundance of females over the 50 year simulation comparing a habitat loss of 600 km^2 over time (by 120 km^2 every 10 years) to a one time 600km^2 loss. These graphs compare abundance of females when loss was focused in the core region

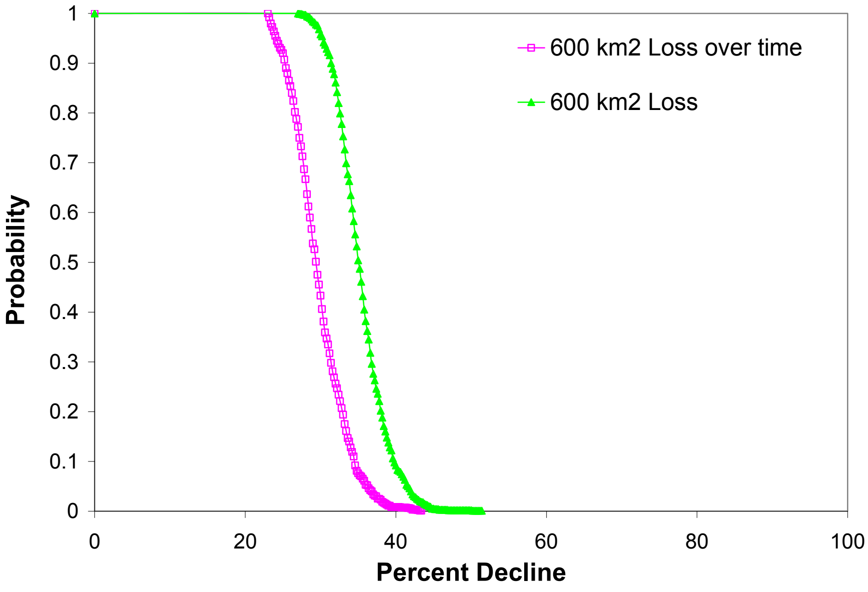

Figure 11. Probability of a percent decline in abundance over the 50 year simulation comparing a habitat loss of 600 km^2 over time (by 120 km^2 every 10 years) to a one time 600km^2 loss. These graphs compare risk when loss was focused in the core region

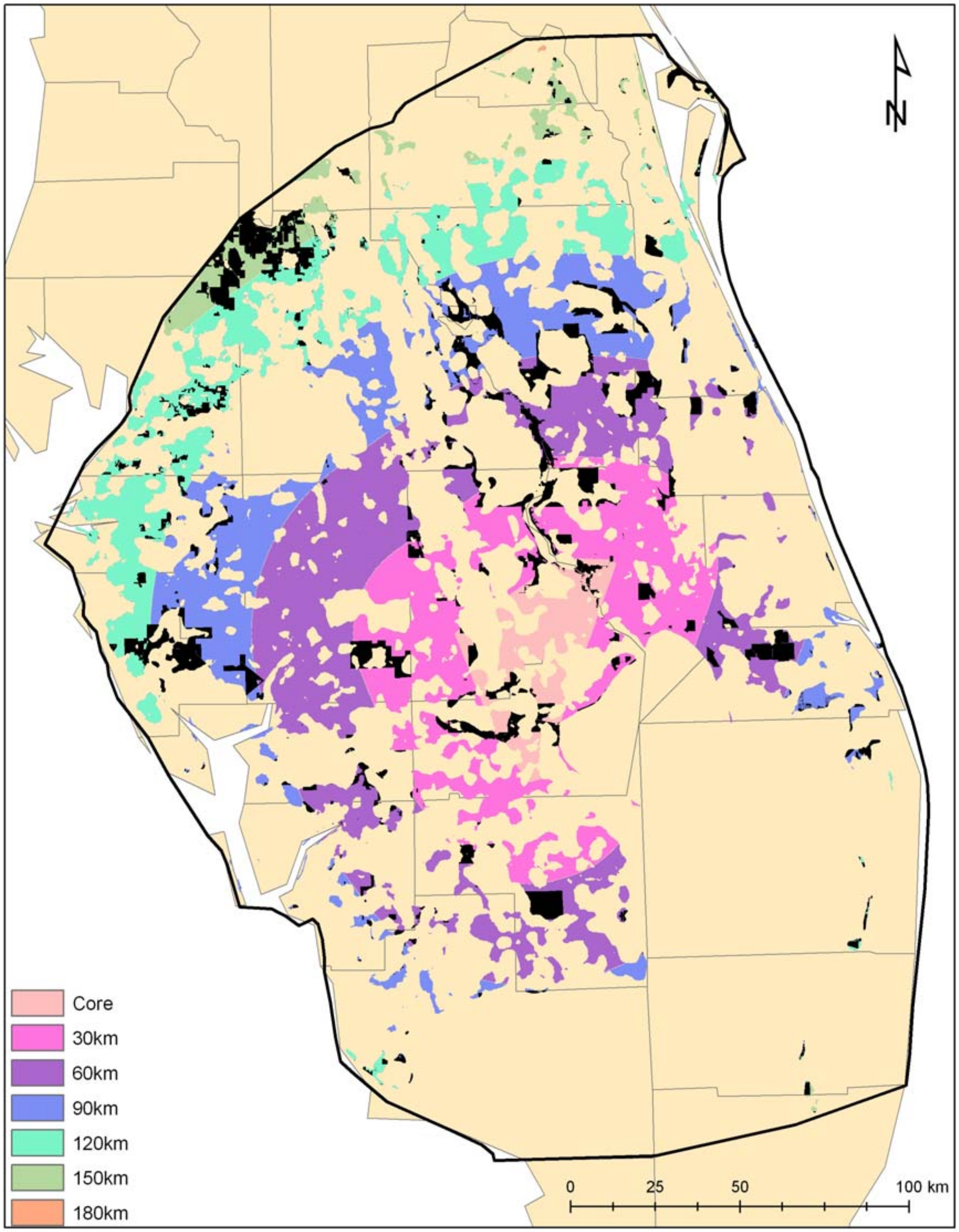

Figure 12. Suitable habitat for the Crested Caracara in Florida, classified as either core habitat or distance within successive 30 km buffers of the core. Areas designated as managed areas by the Florida Natural Areas Inventory that are on suitable habitat are also displayed in black. Outer perimeter of study area is outlined.

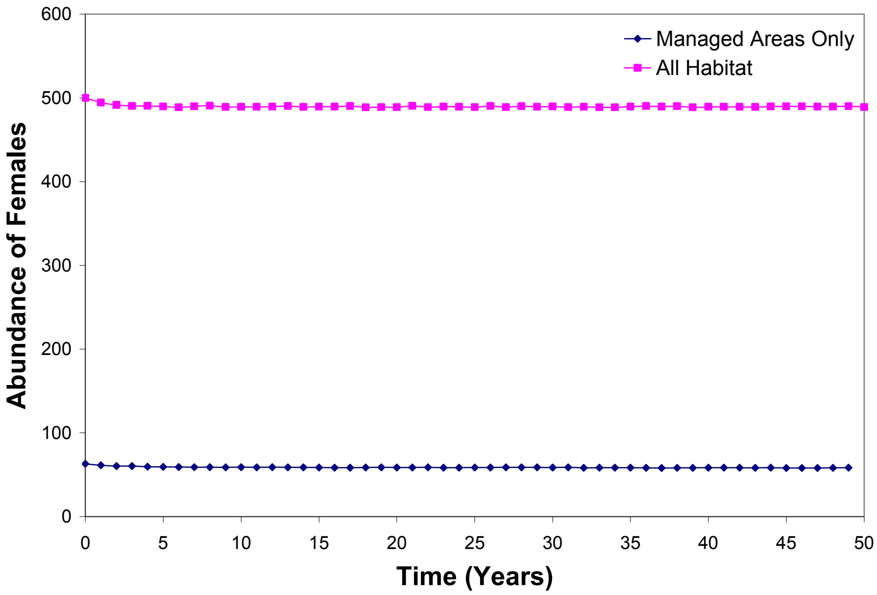

Figure 13. Mean final abundance of females over the 50 year simulation comparing baseline model with no habitat reduction (All Habitat) and reducing habitat to only that amount currently on areas identified as managed areas by the Florida Natural Areas Inventory (Managed Areas Only).

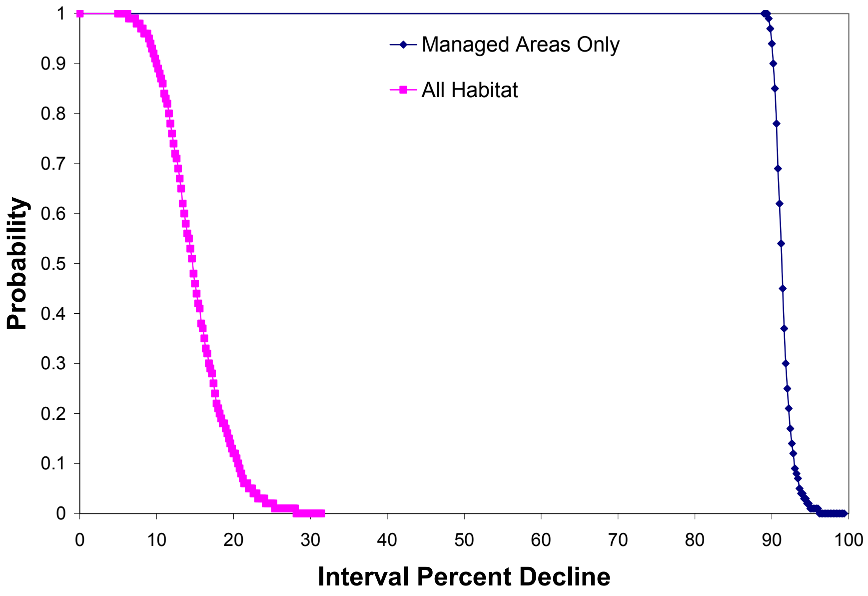

Figure 14. Probability of a decline in abundance over the 50 year simulation comparing baseline model with no habitat reduction (All Habitat) and reducing habitat to only that amount currently on areas identified as managed areas by the Florida Natural Areas Inventory (Managed Areas Only).

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CHAPTER V

GENERAL SUMMARY

In this body of work, we sought to demonstrate an integrated approach linking population demographic, habitat use, and occurrence data for the conservation of the Crested Caracara in Florida. We incorporated demographic and habitat modeling to address three overarching questions. First, based on available data and current conditions in Florida, what is this population's current risk of decline? Second, using a landscape approach, what are the specific landscape features that comprise suitable habitat for the Crested Caracara in Florida? Finally, is all habitat equal, i.e., does the pattern of distribution of suitable habitat and its observed use impact risk of population decline?

In chapter II, our results suggest that the Caracara in Florida is currently stable based on current conditions in Florida, and they are probably not limited by demography but by other constraints such as habitat. Sensitivity analysis conducted by varying all survival and fecundity parameters showed that adult survival had the greatest impact on population persistence, indicating that protection of breeders and their nesting locations is crucial for this population Our perturbation scenarios indicated that this population was relatively resilient, and was able to respond to a restoration of habitat quickly, if conditions are suitable. While we tested multiple model structure of increasing levels of complexity, our most parsimonious model effectively allowed us to look at the relative impact of habitat loss and perturbation over time, as well as assess current status under current conditions. Our results echo the work of others that PVA is especially useful when applied as a simple model to address relative risk, and assess impact of uncertainty (e.g. Beissinger & Westphal 1998; Morris & Doak 2002; Sabo et al 2004). These models support current thinking that protection of habitat is critical, and focus on adult nesting locations is warranted. However, more complex models suggest that understanding the transition between juveniles and adults, and how the specific behavior of each stage influences survival is also important.

In chapter III, our modeling approach showed that heterogeneity, including specific land cover types and water features, was critical in maintaining suitable habitat for the Crested Caracara in Florida. We identified seven important habitat characteristics and defined suitable habitat with a high degree of success. The final predictive habitat model performed very well in both the percentage of test nests accurately categorized as occurring in suitable habitat (81.25%), and in reducing the area judged suitable (27.84% of the study area). Our model seemed to have similar accuracy across the study area, and was not biased by the distribution of the data used in constructing the model. These results can serve as a guide for restoration, mitigation, and other conservation efforts for this isolated population. Determining where and what comprises habitat for the Caracara is especially important due to its small population and apparent dependence on private anthropogenically maintained lands. However, distribution patterns of Caracara in Florida indicate that areas identified as habitat are not used equally across the landscape. This latter observation led to the next analyses.

Traditional methods of modeling habitat rely on analyzing the correlations between ecological characteristics and presence and/or absence data (Guisan & Zimmerman 2000), however some recent studies support the use of abundance to look at disproportionate habitat use across the landscape (Brown et al. 1995; Parra 2006 ; Shkedy & Saltz 2000). The work presented in Chapter IV compliments our earlier development of a predictive habitat model based on presence (Chapter III) by attempting to quantify this differential distribution pattern across the landscape, thus incorporating both of these aspects. We have successfully demonstrated how using occurrence data to quantify patterns of habitat use across the landscape can be useful in generating testable hypotheses and guide research. Using this framework of developing regions with different levels of suitability (by which, we make no inference of quality), we have shown through a variety of simulations that habitat loss likely has different degrees of impact on the population's risk of decline depending on where the loss occurs. With testing and refinement, this method can be used to assess the relative impact of habitat destruction in certain areas compared to others, prioritize conservation efforts, and also identify gaps in our understanding of the Crested Caracara in Florida and its potential impact on population viability.

Novel contributions

While model structure (i.e., number of stages used in the stage matrix) is often suggested as having potential impact on model results, we simply do not see this process being assessed in the literature. Suggestions exist for determination of the number of stages, ranging from complex calculations based on sample size (Moloney 1986; Vandermeer 1978), or stages based on number of years of data collected (Fieberg & Ellner 2001), to a general rule of thumb that simple is better (Morris & Doak 2002). Here we show how multiple stage matrices can be constructed to incorporate available data along with demographic patterns commonly associated with, in this case, bird species, and assessed the utility of these different stage matrices. In our models, this increase in complexity made little difference in our risk assessment, and parsimony prevailed. However, our more complex models demonstrated that the potential impacts of differential survival and fecundity rates within stages (as we modeled be increasing the number of stages) can be estimated and used to determine if additional research attention is warranted.

We suggest that this is a worthwhile exercise in model building, and could be considered as an additional model sensitivity analysis.

In our predictive habitat model, we showed that a successful model, as determined by high rate of accuracy and reduction of the study area, could be constructed using the most commonly available data: presence. This in itself is not novel-- successful models have been built using presence data for other species (Browning et al. 2005; Clark et al 1993; Corsi et al 1999; Thompson et al 2006). However, this model is unique in that each cell in each GIS layer was recoded to reflect the context of the area around it within an average Caracara home range. Context of surrounding habitat has been shown to influence habitat use in other species (Chapa-Vargas et al 2006; Martin et al. 2006; Whitaker et al. 2006). From a modeling perspective this only makes sense to incorporate context of the surrounding area for species that use habitat across multiple units within the analysis (e.g. when resolution is 30m x 30m cells, and a home range is approximately 12.04 km^2). In this research, we show how context can be incorporated in model construction, and this method can be used effectively for any species that is wide ranging and/or territorial.

Finally, we show how occurrence data can be used for those populations that exhibit clustering in their distribution to prioritize areas identified as habitat across the landscape. While this has been suggested as important for other species (Brown et al. 1995) and has been used to identify core habitat in a few other studies (Parra 2006 ; Shkedy & Saltz 2000), we take this a step further. Using buffer areas of biologically relevant size to prioritize habitat around an identified core, we quantified a pattern of habitat use and then linked this demographic model to our new map showing the prioritization scheme. This allowed us to identify the differential impact of habitat loss in various regions on the risk of population decline. This framework could also be applied to other taxa, as long as a scale relevant for the individual species is taken into account.

In conclusion, this work provides a comprehensive approach integrating PVA and GIS modeling for the conservation of the Crested Caracara in Florida. This approach can be incorporated for use in a variety of other species, thus demonstrating the broad applicability of this research to the field of conservation in general.

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APPENDIX I: ANALYSIS OF NEST SITES

Methods—In addition to examining habitat in the home ranges (Chapter III), we also examined the habitat found at the 107 nest site locations (27 nests in known home ranges plus 80 additional nests used in the predictive habitat model evaluation). Using the Point Intersect Tool of Hawth's Tools (Beyer 2004) and the Florida Vegetation and Land Cover layer (FWC 2003), we determined the land cover type at each nest location. We then compared the percentage of nests present in each land cover type to the percentage of each land cover type across the entire study area to test for randomness in nest locations.

Results—Results of the nest site analysis were dramatic. Although improved pasture only comprised 12.5% of the entire study area, 72.9% of the nests were present on this land cover type (Figure 1). The remainder of the nests were located on 13 different land cover types.

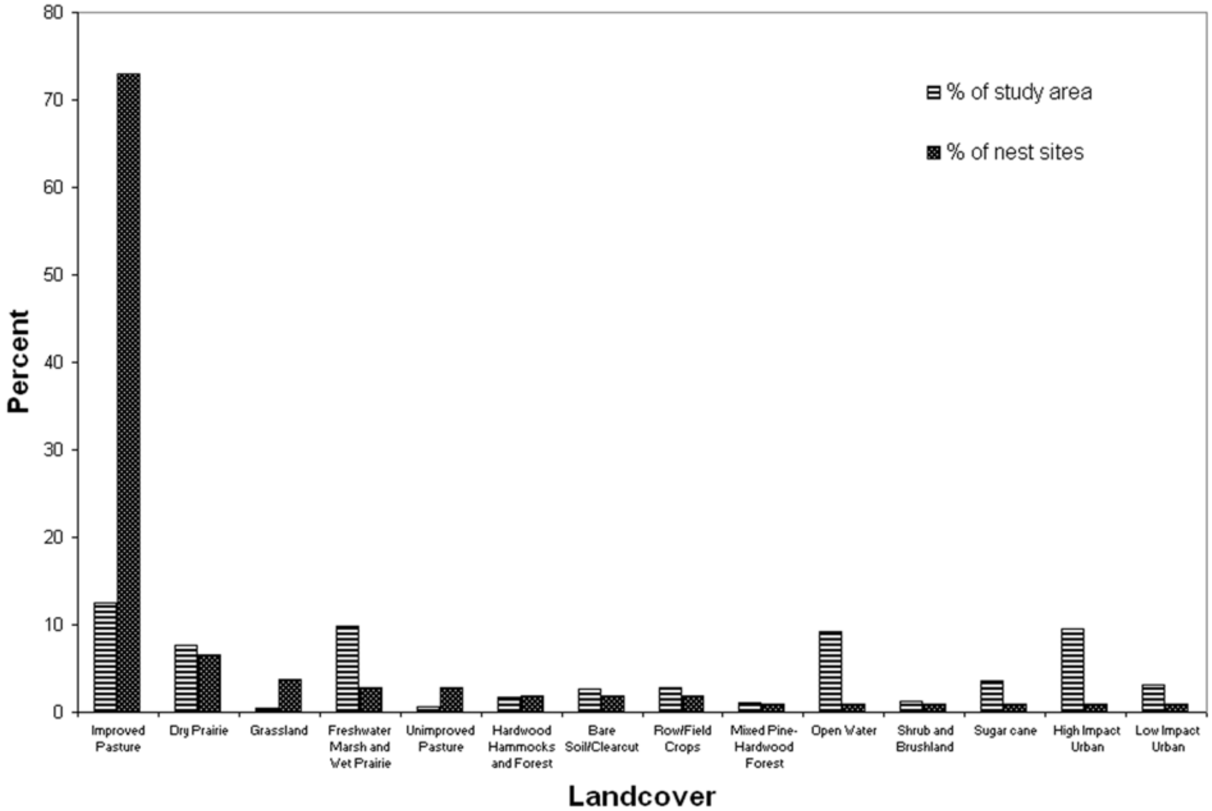

Fig. 1. Percent of Caracara nests ($n = 107$) found in each land cover type (dotted bars) compared to the percent of that land cover type present in the entire study area (striped bars). Land cover types are those identified by the Florida Fish and Wildlife Conservation Commission in the 2003 Florida Land Cover Layer (FWC 2003).

APPENDIX II: BOOLEAN HABITAT MODEL

METHODS

In GIS, Boolean models are those in which attributes are given a binary score, usually 0 or 1. In habitat suitability studies, these values are most often used to describe unsuitable (0) and suitable (1) habitats. In the current study, each cell of every layer was scored in this manner. The Boolean model used the same seven layers significantly correlated with Caracara presence in Florida as those used to construct the predictive models described in Chapter III: Improved Pasture, Unimproved Pasture, Grasslands, Cabbage Palm/Live Oak, Hardwood Hammocks and Forest, Lotic water, and Lentic water. To be classified as suitable, the value of a cell was required to fall within the range of values observed in the 28 actual home ranges (Table 1). Using the Raster Calculator of ArcGIS, we then summed these layers to produce a final Boolean model. If a cell satisfied all of the criteria of the model, then it received a value equal to the number of data layers (most suitable = 7). We constructed additional models to show areas where only 1 of the layers did not meet the conditions of the first model. These models are useful in predicting what may be limiting the suitability of habitat for the Crested Caracara in Florida.

RESULTS

As stated above, if a cell satisfied all of the criteria of the model, then it received a value equal to the number of data layers used and would be considered most suitable, whereas a cell meeting none of the criteria scored a value of zero and would be considered least suitable. Within the study area, values for the Boolean model ranged from 3 to 7, where 7 was the maximum score and met all criteria (Table 2). That is, in the 12.04 km^2 neighborhoods surrounding each cell, 3 to 7 of the vegetation and water types are found in proportions similar to that in the 28 Caracara home ranges. Evaluation of the model found that using a cutoff value of 6 (a cell meets the criteria for *any* 6 layers of the 7 that we used) for determining suitable habitat correctly classified all but 4 of the test nests (95%), but reduced the amount of area classified as suitable by only 30% (Table 2). Using the highest suitability value of 7 resulted in a more discriminatory model (reduced study area by 56%, but accurately classified less nests (63.75%) than using a cut-off value of 6 (Table 2).

More than any other single habitat characteristic, the amount of Hardwood Hammocks and Forest (Table 3) limited more cells from scoring a value of 7 (i.e., 9015 km^2 met all other criteria except Hardwood Hammocks and Forest). Conversely, only a very small number of cells did not receive a value of 7 due to the amount of unimproved pasture in their neighborhood (i.e., only 43 km^2 met all other criteria except unimproved pasture) (Table 3).

Table 1. Data layers that were significantly different between actual versus simulated home ranges (*n* = 28) for Crested Caracaras in south-central Florida. The minimum and maximum values were used to construct the Boolean model of Caracara habitat suitability by assigning cells as suitable (1) or unsuitable (0).

Data Layer	Minimum Value	Maximum Value
Cabbage Palm - Live Oak Hammock	0%	6.93%
Grassland	0%	15.4%
Improved Pasture	0%	80.32%
Unimproved Pasture	0%	29.83%
Hardwood Hammocks and Forest	0.5%	14.74%
Lentic Water	2.93%	47.21%
Lotic Water	0.17 km/km^2	6.11 km/km^2

Table 2. Results of the Boolean model to evaluate habitat suitability for Crested Caracaras in south-central Florida. Reduction in area and test nests accurately classified are shown for each value of the Boolean model, if that value was used as a baseline value for suitability, i.e. if all areas valued at 6 or above are considered suitable, this would reduce the study area by 30% and accurately predict 95% of nest nests (*n*=80)

Boolean Value	Reduction in Area (%)	Test Nests Accurately Classified (%)
≥ 3	0%	100%
≥ 4	0%	100%
≥ 5	9%	100%
≥ 6	30%	95.0%
7	56%	63.75%

Table 7. Area precluded from receiving a value of 7 (meets all characteristics within limits of known Caracara home ranges) in the Boolean model by each of the data layers. This is a result of the neighborhood having a greater or lesser amount of the vegetation or water than required to satisfy the model (see Table 1).

Data Layer	Area (km^2)
Unimproved Pasture	43
Improved Pasture	44
Cabbage Palm - Live Oak Hammock	68
Grasslands	506
Lotic Water	924
Lentic Water	5347
Hardwood Hammocks and Forest	9015

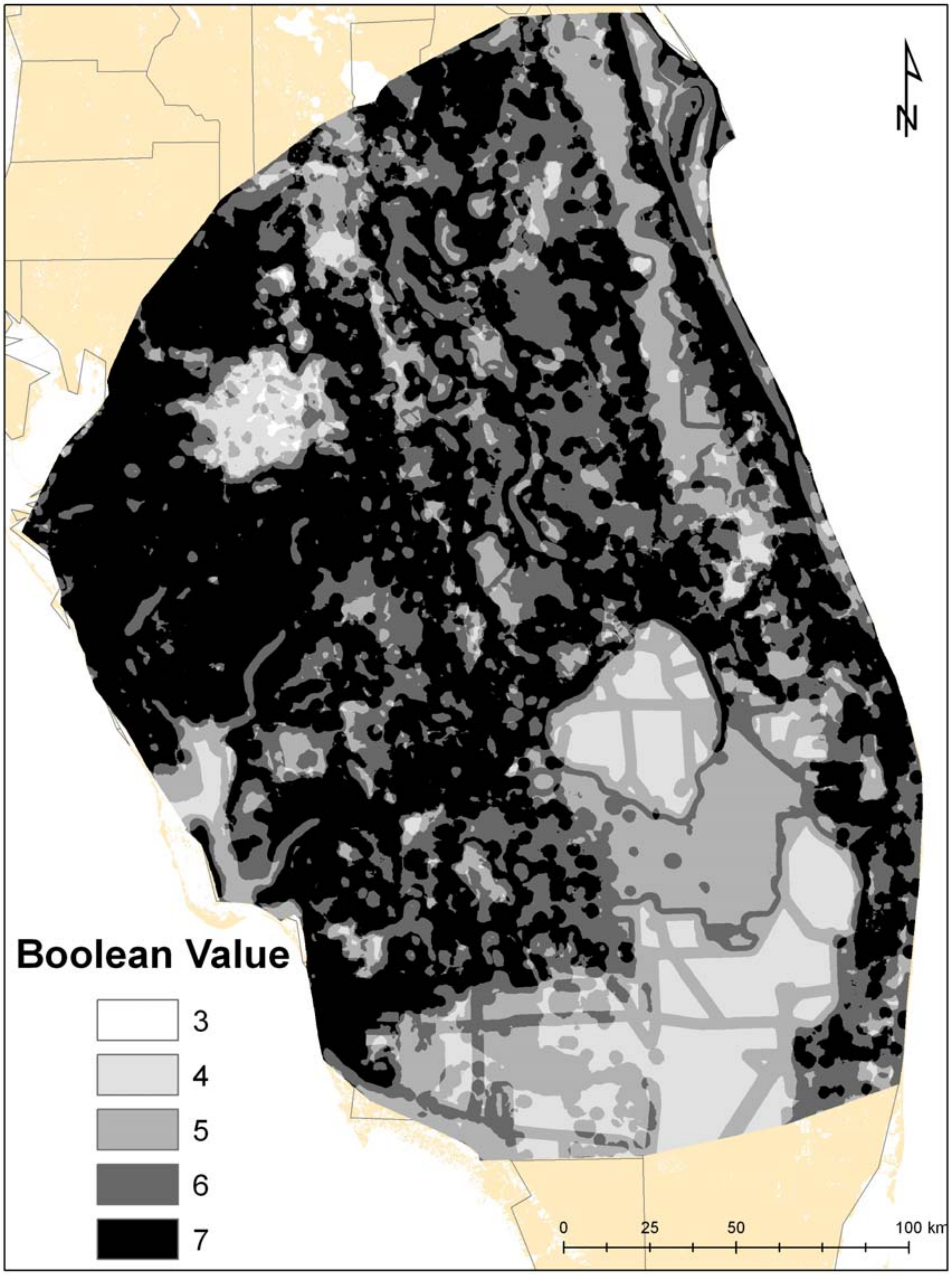

Figure 1. Boolean model of Crested Caracara habitat suitability in Florida. Values (3 through 7) indicate the number of criteria each pixel meets by matching the landscape composition found in actual Caracara home ranges. A value of 7 indicates that the pixel meets all criteria for suitability. For a description of the 7 land cover types and their proportions used to determine suitability, see Table 1.