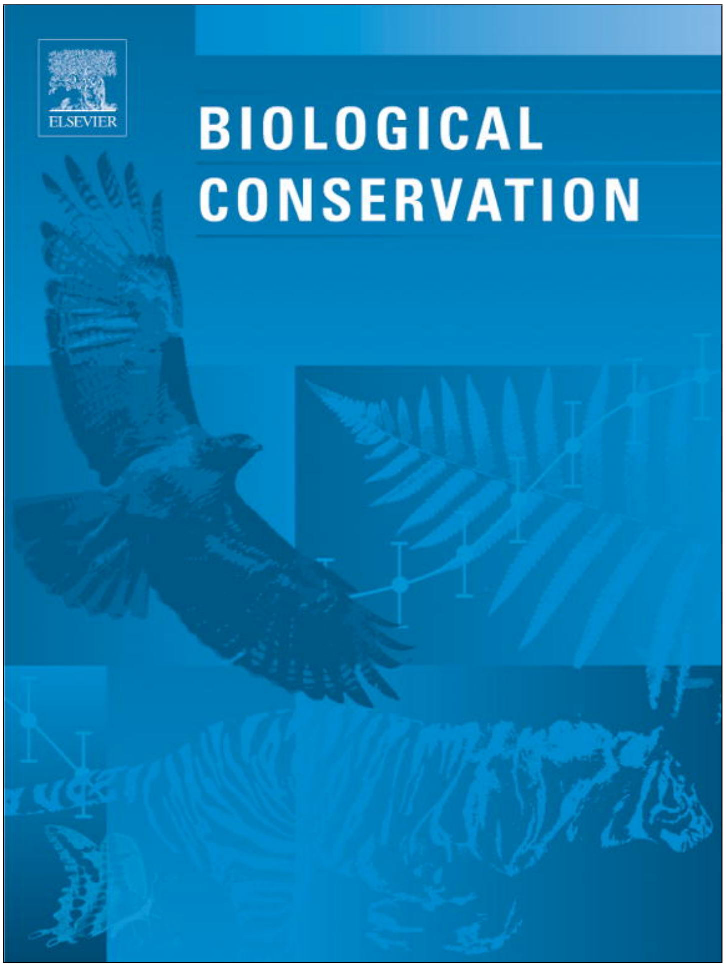
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Examining the knowing–doing gap in the conservation of a fire-dependent ecosystem

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A B S T R A C T

Scientifically informed conservation goals do not always align with what is accomplished in practice, leading to the so-called "knowing–doing gap". One reason why the knowing–doing gap exists may be that scientific recommendations often do not account for the "real-world" social context of conservation. The social context may be particularly important for ecosystem restoration involving prescribed burning. In the longleaf pine ecosystem, scientists and conservationists have called for large-scale restoration using prescribed burning; however, recent levels of burning may be insufficient to accomplish restoration. We studied the knowing–doing gap in the longleaf pine ecosystem by investigating where recent burns had been conducted. We used spatio-temporal logistic regression to relate recent burning in the Onslow Bight, North Carolina, to site and landscape attributes that burn practitioners there had previously said were important. Our results show that prescribed burns were preferentially placed on high-quality sites rather than on degraded sites, suggesting a knowing–doing gap in longleaf pine conservation in which burning is not used for restoration. In addition, sites that had not been burned for at least 4 years showed an increased probability of burning as distance from development increased, suggesting that sites with high fuel loads near development were not likely to be burned. Finding ways to encourage burning on degraded sites near development, such as rewarding practitioners for successfully conducting difficult burns, would help narrow the knowing–doing gap in conservation of this and other fire-dependent ecosystems.

1. Introduction

When scientifically informed conservation goals do not align with what is accomplished in practice, the so-called "research-implementation" or "knowing–doing" gap occurs (Knight et al., 2008). This gap has been recognized in a number of disciplines within and related to conservation science, including conservation planning (Knight et al., 2008), restoration ecology (Higgs, 2005), and invasion ecology (Esler et al., 2010). One reason why the knowing–doing gap exists is because conservation research may not reach practitioners (Fazey et al., 2005; Knight et al., 2008). This issue has been widely acknowledged and many efforts are underway to promote closer communication between scientists and practitioners (e.g. Anonymous, 2007). Another reason why the knowing–doing gap exists may be that the goals or recommendations resulting from research do not take into account the "real-world" social context of conservation. The importance of considering conservation's social dimension when setting goals has been recognized by conservation biologists recently because social factors can constrain the opportunities available to implement conservation actions (Knight et al., 2006, 2010).

In fire-dependent ecosystems, the social context of conservation can affect what can be accomplished through limitations related to the costs, risks, and logistical challenges associated with fire use. Constraints such as the cost of implementing prescribed burning and shortage of trained personnel can limit the use of fire (Cleaves et al., 2000). In addition, there is potential for damage to human health or property if smoke or fire spread to populated areas. In landscapes that contain a mixture of protected, residential, and commodity producing lands, fire use is particularly constrained because of the wildland–urban interface (WUI). The WUI is defined as the area where homes and other structures meet or intermix with natural vegetation. In the WUI, fear of liability for damage to human health or property could decrease the likelihood of letting wildfires burn or using prescribed fire, especially because residents tend to have negative perceptions of fire use as a management tool (Winter and Fried, 2000; McCaffrey, 2004; Schindler, 2007). Conversely, suppressing wildfires or failing to implement burning also carries longer-term increase in risk of negative effects from future

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wildfires because of fuel accumulation. Avoiding short-term damages that could result from fire use in some locations may be more compelling to land managers than conducting fire management, which may have benefits that are poorly quantified and realized over the long term (Maguire and Albright, 2005; Donovan and Brown, 2007). All of these factors in concert can limit fire use, result in few conservation accomplishments in the long-term, and bring further ecosystem degradation (Stankey et al., 2003).

In the longleaf pine (*Pinus palustris*) ecosystem in the southeastern United States, there is a difference between stated goals and actual accomplishments in fire use for conservation. A major conservation goal for the longleaf ecosystem is large-scale management using prescribed fire to restore and maintain the rich diversity of plant and animal species found there (America's Longleaf, 2009). Indeed, more burning is done in the Southeast than in any other part of the country (Haines et al., 2001). However, several challenges, along with the ones described previously, likely present limitations to burning in longleaf pine ecosystems. With increased time since the last burn in the ecosystem, plant growth and pine needle accumulation in the understory, along with infill of woody plants in the midstory, lead to a buildup of fuels and increased potential for higher intensity fires (Varner et al., 2005). In addition, the Southeast as a whole also contains the largest land area in the WUI (Radeloff et al., 2005). Researchers have suggested that current prescribed burning programs are not accomplishing ecosystem-wide restoration of longleaf pine (Van Lear et al., 2005). This shortcoming is in part because the overall amount of prescribed burning is insufficient to burn large extents with a frequent return interval (Van Lear et al., 2005). The overall amount burned is often limited by lack of funding or other resources (Cleaves et al., 2000). It is also important to establish whether fire managers are able to place the burns they do conduct on sites that are in need of restoration. Avoidance of challenges, risks and conflicts associated with burning may be as influential in determining whether a site is burned as the site's ecological condition. For example, fire managers may be inclined to conduct burns on areas they know they will be able to burn in the future, rather than burning larger areas that may not be feasible to maintain. Examining where burns have been conducted will inform strategies for ensuring that prescribed burning accomplishes regional longleaf pine restoration.

We examined recent burning of the longleaf pine ecosystem by land management agencies in the Onslow Bight region of North Carolina (NC), a region containing a mix of urban, residential, and commodity-producing lands in which stakeholders previously acknowledged the need for restoration of longleaf pine via prescribed burning. Our objective was to investigate which site and landscape attributes best explained the placement of prescribed burns in order to determine whether prescribed burning was being conducted in areas in need of restoration. We posed the following three questions relating to the placement of prescribed fire and the knowing–doing gap in restoration of longleaf pine within protected areas across the region:

1. Have recent prescribed burning activities focused on maintaining sites in good ecological condition, or on restoring poor-quality sites?
2. Which site and landscape attributes related to non-ecological factors such as human health and commodity production contribute to determining whether a site is burned?
3. How much influence do these non-ecological attributes have on burning, compared with ecological attributes?

We hypothesized that prescribed burning activities have focused on maintaining high-quality sites because of the risks associated with burning poor-quality sites, where fuel loads are usually higher. Because of previous research showing that risks of prescribed burning are high in the WUI, we also hypothesized that location of the WUI was a major non-ecological factor in determining which sites were burned. Specifically, we predicted that sites located farther from the WUI were burned more often than sites closer. Finally, we hypothesized that non-ecological attributes of sites and surrounding landscapes were more important than ecological attributes in determining which sites would be burned because of the challenges non-ecological factors present for conducting burns. Investigating the factors associated with the placement of prescribed burns in the longleaf pine ecosystem will help us identify relevant strategies for accomplishing conservation goals in this important ecosystem.

2. Methods

2.1. The longleaf pine ecosystem and conservation

The longleaf pine ecosystem was once the dominant habitat in the southeastern US along the coastal plain and outer piedmont from Texas to Virginia (Frost, 1993). When frequently burned (every 1–3 years), the understory communities in longleaf pine ecosystems have among the highest levels of plant species richness of any ecosystem in the world (up to 40 species per m^2 and 140 species per 1000 m^2, Peet and Allard, 1993). Due to widespread timber harvesting, fire suppression, and development, longleaf pine forests have been severely degraded and fragmented, reducing this forest type to only 3% of its pre-European settlement range (Frost, 1993). As a result, populations of plant and animal species that depend on longleaf pine habitat, including the Federally-endangered Red-cockaded Woodpecker (*Picoides borealis*) have declined (Van Lear et al., 2005). This decline has prompted Noss and others (1995) to designate longleaf ecosystems as "critically endangered," and others to call for large-scale restoration efforts involving prescribed burning to conserve and restore habitat connectivity (Landers et al., 1995; Hoctor et al., 2006).

2.2. The Onslow Bight region

The Onslow Bight is a 1 million ha region of the North Carolina (NC) coastal plain (Fig. 1) where a multiagency partnership has been established for conservation of the longleaf pine ecosystem. Prior to European settlement, an estimated 48% of the Onslow Bight was covered in longleaf or mixed pine habitat, much of it wet or mesic longleaf pine–wiregrass savanna (Frost and Costanza, unpublished data). Today, approximately 19% of the landscape is longleaf pine (Southeast Gap Analysis Project, 2008). Managed pine plantations cover 22% of the Onslow Bight, and 21% is either developed or has been converted to agriculture (Southeast Gap Analysis Project, 2008). Major public landholdings comprise 15% of the Onslow Bight and include US Marine Corps Camp LeJeune and Cherry Point (US Department of Defense), Croatan National Forest (US Forest Service), Cedar Island National Wildlife Refuge (NWR, US Fish and Wildlife Service), and several designated game lands (NC Wildlife Resources Commission, NC WRC). The Nature Conservancy (TNC) also manages 1% of the land in the Onslow Bight. These six land management agencies have joined to form the Onslow Bight Fire Partnership (OBFP) to increase the capacity for prescribed burning (OBFP, 2005).

2.3. Prescribed burn data

We compiled GIS data delineating the locations of prescribed burn compartments and prescribed burns conducted between 1989 and 2007 from the six Onslow Bight land-management agen-

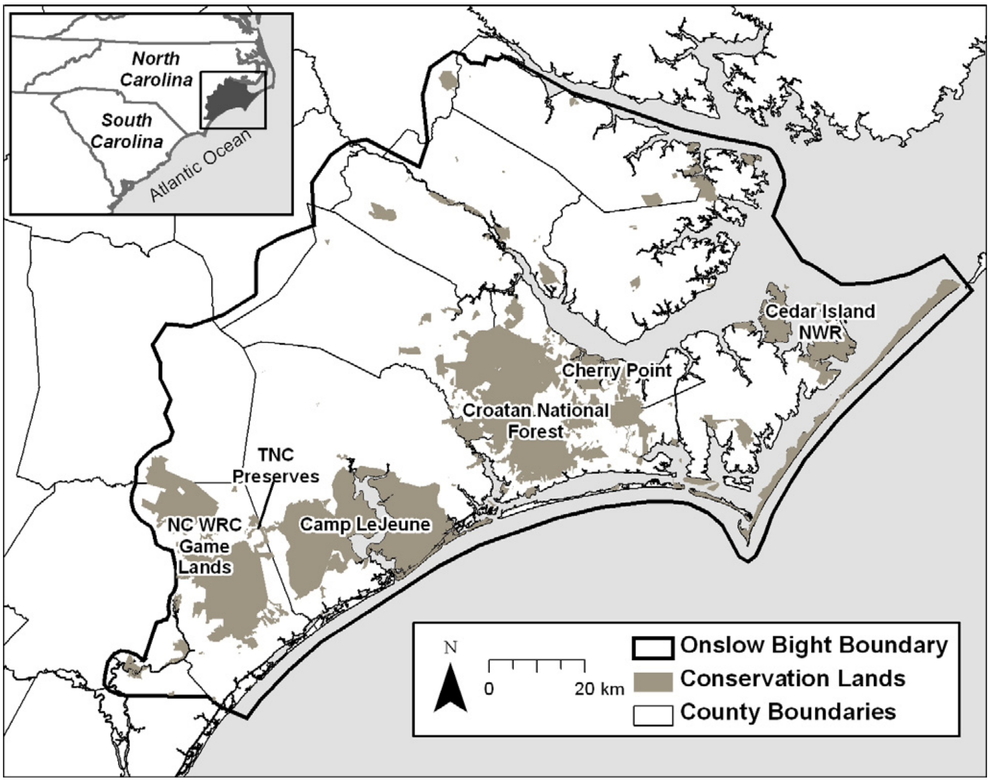

Fig. 1. Onslow Bight study area, showing the locations of the six management agencies included in this study. NC WRC stands for North Carolina Wildlife Resources Commission, TNC stands for The Nature Conservancy, and NWR stands for National Wildlife Refuge.

cies that manage their land via prescribed burning. These burn compartments represent parcels of land that are managed by an agency as a single unit for burning, but some have never been burned. Hereafter, we will refer to burn compartments as "sites". We used soil survey data (SSURGO, Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture, 2008) to select only sites in our GIS data predominantly on soils with relatively low organic matter content—the soils that support longleaf pines. Thus, we included sites that currently support longleaf pine communities or that could realistically be restored to longleaf. The result was a set of 691 sites covering a total area of 52,226 ha.

In addition to the six agencies listed above that conduct prescribed burning on conservation land in the Onslow Bight, other entities such as the NC Division of Forest Resources and several contractors conduct prescribed burning on privately owned lands. However, the spatial accuracy of their burn records was unsuitable for this analysis.

Records of prescribed burning were in the form of GIS polygon data delineating burned areas from 1989 to 2007, which fell within but were not necessarily contiguous with site boundaries. Prescribed burning in longleaf pine ecosystems began in the late 1980s and early 1990s (Pyne, 1997); therefore, the majority of prescribed burning history is likely captured in the records we compiled. Because results from previous surveys of stakeholders indicated that a site's burn history over the previous 15 years was an important criterion for determining whether a site would be burned (Costanza and Moody, 2011), we used records for those years that were preceded by at least 15 years of burn history data (2004–2007) as the response variable in regression analysis. For this response variable, for each year during the period 2004–2007, we labeled a site as "burned" for a given year if 50% or more was burned, thus maximizing the chance that sites designated as "burned" corresponded to actual management decisions made for those sites, and did not result from nearby fires burning into adjacent sites.

2.4. Spatial analysis of predictor variables

We previously surveyed stakeholders in the Onslow Bight landscape to determine how the attributes of a given site and its surrounding landscape affect decisions about whether or not to burn that site (Costanza and Moody, 2011). In that survey, respondents indicated the ecological and non-ecological attributes that they use as criteria to prioritize sites for prescribed burning (Table 1). We divided the stakeholder-identified attributes into two groups for this analysis. Ecological attributes described the ecosystem of the site or its surrounding landscape, while non-ecological attributes were predominantly related to the legal or logistical challenges associated with burning. We recognize this division is imperfect because some attributes in each of these categories are likely correlated with those in the other category, and some may represent both types of characteristics, but we have categorized them according to their main relevance.

We developed spatial data based on existing GIS data sets representing all of these attributes to use as predictors in our analysis (see Table 1 for predictors and sources). The only attribute used by stakeholders that was excluded in our analysis was the locations of invasive species, because a comprehensive, spatially explicit assessment of invasive species locations has not been done in the region (Buchanan, NC Natural Heritage Program, pers. comm.). Four of the modeled predictors varied for any given site over the 4-year period 2004–2007 (Table 1). These were: the number of years since the previous burn, the number of times each site burned over the 10 years prior, the distance from each site to the nearest site that had been burned in the previous 5 years, and

Table 1
Criteria for decisions about prescribed burning (from Costanza and Moody (2011)), and corresponding site attributes used as predictor variables in this analysis.

Criterion	Site attribute (predictor variable)	Source	Varies by year
Ecological			
Ecosystem health	% Canopy cover, 2001	LiDAR (Breckheimer et al. unpublished)	No
	% Midstory cover, 2001	LiDAR (Breckheimer et al. unpublished)	No
	Number times site was burned in 10 years prior	Agency prescribed burn records	Yes
Frequent presettlement fire	Proportion of site with soils that may have supported wet or mesic longleaf pine	Crosswalk of SSURGO soils (Frost and Costanza, unpublished)	No
Red-cockaded Woodpeckers	Distance from active clusters (nesting areas), 2001	NC Natural Heritage Program	No
	Distance from inactive clusters (nesting areas), 2001	NC Natural Heritage Program	No
	Distance from foraging habitat, 2001	LiDAR (Breckheimer et al. unpublished)	No
Threatened or endangered species	Distance from threatened or endangered plants and animals that depend on fire	NC Natural Heritage Program; invertebrates: Hall et al. (1999) plants: Buchanan and Finnegan (2008)	No
Non-ecological			
Firebreaks	Distance from stream locations	NC Center for Geographic Info. and Analysis	No
	Area of site	Agency burn compartment GIS data	No
Firebreaks/proximity to other burned areas	Distance to the nearest site that was recently burned (within the last 5 years)	Agency prescribed burn records	Yes
Timber	Proportion of site in managed pine plantations, 2001	Southeast Gap Analysis Project (2008)	No
Time since last burn	Number of years since last burn	Agency prescribed burn records	Yes
	Proportion of site that was never burned	Agency prescribed burn records	Yes
Wildland–urban interface	Distance from developed land, 2001	National Land Cover Database (Homer et al., 2007)	No
	Distance from road locations	NC Department of Transportation	No

the proportion of the site that was never burned. We used records of prescribed burning to create these three burn history predictors. The rest of the metrics used as predictor variables were derived from static GIS data representing conditions at one point in time before 2004 (Table 1). All of the data layers representing site attributes were produced as rasters with a resolution of 30 m. All GIS operations were performed in ArcGIS 9.3.1 (Environmental Systems Research Institute [ESRI], 1999–2010).

2.5. Statistical analysis

We used logistic regression to answer our three research questions. The response variable was the binary variable indicating whether each site was burned or unburned each year from 2004 to 2007. The modeled attributes for each site were used as predictor variables. All were continuous variables, with the exception of the time since last burn, which was treated as a variable with four categories: 1 year, 2–3 years, 4–5 years, and >5 years to simplify interpretation (Table 2).

Because the burn status of sites was followed over time, the data in this study consist of repeated measurements on the same site, and separate measurements on different sites. Such a design can lead to correlation among observations coming from the same site if a site's burn status in a given year affects the decision to burn in following years. In addition, potential spatial autocorrelation can exist if the decision to burn one site is correlated with burning on a nearby site. To account for spatial and temporal correlation we ultimately used the method of generalized estimating equations (GEEs) to fit a population-averaged model to the data (Zeger et al., 1988) and a user-specified correlation matrix that incorporated both types of correlation. However, we began by using generalized linear models (GLMs) and generalized additive models (GAMs), which do not account for correlation, because these allow examination of non-linear relationships and higher-order interactions.

To answer our first question about whether burning was focused on maintaining high-quality sites or on restoring poor-quality sites, we first fit a model using ecological predictor variables. We started with a GLM using a binary distribution and a logit link. We conducted model selection manually, systematically examining all possible combinations of predictors. Because the pool of possible predictors came from attributes that burn practitioners had said were important, there was a low risk of fitting a model using a set of predictors that was not meaningful. We looked for non-linear relationships by fitting a GAM using smoothed splines for each of the predictors, and added higher-order terms to the GLM model where needed. We checked for statistically significant interactions between any two variables, and included those interactions only where ecologically meaningful.

When we had determined the optimal model using GLM, we used GEE to fit a spatio-temporal correlation model to the data using the set of predictors. When a non-linear link function is used in a GLM, as was the case here where a logit link was used, and a population-averaged interpretation of the regression parameters is desired, a method such as GEE is preferred over fitting a mixed effects model (Fieberg et al., 2009). Before fitting the GEE, we used the Pearson residuals from the final binary GLM to assess the presence of any lingering spatial and temporal correlation. We first estimated the average temporal correlation at sites and then determined how that temporal correlation was diminished by spatial extent, similar to approaches taken by Gumpertz et al. (2000) and Lin (2010). This approach makes the assumption that the spatio-temporal correlation can be decomposed into separate spatial and temporal components, and has the advantage of yielding a simpler analysis than estimating both types of correlation jointly.

We estimated a 4×4 unstructured temporal correlation matrix R_T by calculating the ordinary correlations of the residuals from the same site but from different years (Appendix A). We then estimated the spatial correlation of the residuals empirically by obtaining cross-semivariograms for all individual years and pairs of years, then approximating the empirical semivariograms with a mixed effects model (see Appendix B for semivariograms and information about how we approximated them). From the mixed effects model estimates we obtained corresponding exponential correlograms, and using the matrix of pairwise distances between plots, we constructed the 691×691 spatial correlation matrix R_S.

Table 2
All variables included as predictors, and results of Wald tests for significance of variables used in three optimal GEE models.[a] The *p*-values indicate the significance of each predictor when it was added to a model containing all other variables that were included in the optimal model.

	Ecological		Non-ecological		Both	
	X^2	p	X^2	p	X^2	p
Dist. from active Woodpecker clusters	17.6	<0.001			11.2	0.001
Dist. from inactive Woodpecker clusters	0.1	0.80			20.2	<0.001
Dist. from inactive Woodpecker clusters^2	8.7[b]	0.003[b]			NA	
Dist. from T&E species	6.1	0.01			NA	
Midstory cover	35.7	<0.001			19.9	<0.001
Canopy cover	15.4	<0.001			8.1	0.004
Prop. experiencing frequent presettlement fire	NA				NA	
Prop. Woodpecker foraging habitat	NA				NA	
Number of burns in last 10 years	NA				NA	
Area (ha)			4.5	<0.001	8.2	<0.001
Time since last burn[c]			14.5	0.002	16.4	<0.001
Dist. from road			1.0	0.3	2.6	0.1
Prop. in managed timber			3.6	0.05	4.9	0.03
Prop. never burned			24.2	<0.001	21.1	<0.001
Dist. from recent burn			12.5	<0.001	8.0	0.005
Dist. from development			0.9	0.4	2.4	0.1
Dist. from development: time since last burn[c]			16.4	<0.001	11.9	0.007
Dist. from stream			NA		NA	

[a] "NA" indicates the variable was included in the pool of possible predictors for a given model, but was not included in the optimal model.
[b] Both a linear term and a quadratic term were included for this variable. The Wald test compares a quadratic model against a linear model.
[c] Variable is categorical. The reported Wald statistic has an asymptotic chi-squared distribution with three degrees of freedom. All of the other reported Wald tests are one degree of freedom tests.

Once we had constructed R_T and R_S, we made sure that they satisfied constraints imposed for the predicted probabilities of a pair of binary response variables (see Appendix C, Prentice, 1988; Chaganty and Joe, 2004). We obtained the final working correlation matrix by taking the Kronecker product $R_S \otimes R_T$ to yield a 2764×2764 spatio-temporal matrix R_{ST} and used R_{ST} as the working correlation matrix in a GEE. We calculated estimates of the regression parameters using Newton's method, and this estimation was iterated until convergence (Appendix C).

To answer our second question about the influence of non-ecological attributes on prescribed burning, we repeated the steps outlined above to select a model using only non-ecological attributes and fitted a spatio-temporal correlation model with GEE. To answer our final question about the relative influence of ecological versus non-ecological attributes on burning, we used the same approach to construct a model that incorporated both ecological and non-ecological variables, starting with the pool of predictors that were significant in the first two models. For all models, cross-semivariograms and temporal correlations showed similar patterns. We compared the optimal models for each of the three pools of predictors using QIC_u, a modified version of AIC that can be used with GEE (Hardin and Hilbe, 2003). We also compared the areas under the curve (AUC) for the three models. To discriminate between model predictions of incidence versus non-incidence of burning, we used the minimized difference threshold as a cutoff because under- and over-prediction were equally undesirable (Jimenez-Valverde and Lobo, 2007).

All statistical analyses were done using R software (R Development Core Team, 2009), along with the contributed packages mgcv (Wood, 2006), nlme (Pinheiro et al., 2009), gstat (Pebesma, 2004), and ROCR (Sing et al., 2005).

3. Results

On average, during the period 2004–2007, the six management agencies burned 8256 ha of longleaf pine habitat annually (16% of longleaf pine sites; the range was 14–17%). For each of the three pools of predictors, ecological, non-ecological, and both sets, model selection using GLM followed by spatio-temporal GEE resulted in optimal models (Table 2). The temporal correlation observed in the unstructured correlation matrices for each model is explained by the fact that when a site is burned, it is less likely to be burned the next 2 years, but more likely to be burned after 3 years (Appendix A). The spatial correlation structure we included in the GEE model captured the autocorrelation present in the GLM residuals (Appendix B). In the GEE with spatio-temporal correlation, some of the predictors that were significant in the GLMs were no longer significant after we accounted for correlation (Table 2).

We used the coefficients from the models with only ecological predictors and only non-ecological predictors to calculate odds ratios, or the factor change in odds of being burned with a specified change in the value of a predictor (Figs. 2 and 3; see Appendix D for coefficient estimates). In the model with ecological predictors, for every 1 km farther away from an active Red-cockaded Woodpecker cluster (nesting area), odds of burning decreased by a factor of 0.92 (Fig. 2). Similarly, odds of burning a site decreased for sites farther from threatened and endangered species of plants and invertebrates, and with increased midstory cover. Sites that were farther from inactive Red-cockaded Woodpecker clusters (clusters that had been abandoned by Woodpeckers) had increased odds of being burned and the relationship was quadratic. Sites with higher canopy cover also had increased odds of being burned.

In the model with non-ecological predictors, odds of burning decreased with the proportion of a site managed for timber, the portion of a site that had never been burned, and distance from a recent burn (Fig. 3). Odds of burning increased with area of sites, and with distance from a road. There was a significant interaction between distance from development and the time since a site had last been burned. The effect was significant for sites that had last been burned 2–3 or 4–5 years prior. In the category of 2–3 years since burn, sites that were closer to development had a higher probability of burning, while in the category of 4–5 years since burn, sites that were farther from development had a higher probability. Probability of burning also increased with distance from development for sites that had burned 1 year prior or greater than 5 years prior, but the effect was not significant in those cases.

The full model with both ecological and non-ecological predictors had coefficients that were similar to those of the other two models (Appendix D), and thus the odds ratios of predictors were similar. However, in the full model, the distance from threatened or endangered species was no longer significant, the proportion of a site that was managed for timber became significant, and distance from inactive Woodpecker clusters no longer showed a quadratic relationship (Table 2).

The model using non-ecological predictors performed better than the model with ecological predictors (AUC = 0.71 and 0.67, QIC_u = 2127.6 and 2195.3 respectively). The model with both types of predictors performed better than each of the other two (AUC = 0.73 and QIC_u = 2094.1).

4. Discussion

We analyzed recent prescribed burning in the longleaf pine ecosystem in order to examine the difference between conservation goals and implementation of burning. We determined the site attributes associated with placement of recent burns. Our results highlight the joint influence of ecological and non-ecological attributes of sites and their surrounding landscapes on determining burning placement, and also reveal that prescribed burns were preferentially placed on sites that were already in good condition.

The optimal model incorporating ecological attributes alone, without non-ecological attributes, suggests that sites in better ecological condition were more likely to be burned. Sites that were closer to active Red-cockaded Woodpecker clusters and threatened or endangered species occurrences, those that were farther from inactive clusters, and those with lower midstory cover and higher canopy cover had increased odds of being burned. Sites with highest canopy cover in the Onslow Bight are both naturally-regenerating and planted loblolly and longleaf pine stands, while low canopy cover sites are recent clearcuts; therefore, our results for this predictor indicate that burning was more likely in forested stands. Results for the other predictors suggest that prescribed burning was more likely to be used for maintenance of high-quality habitat, rather than for ecological restoration on low-quality sites, and are consistent with our hypothesis. Sites with habitat that can support Woodpeckers and those with lower midstory cover have less fuel accumulation. Thus, burns are easier to implement on these sites, there is less need for prior treatment before burning, and there is less potential for high intensity fires that can damage the ecosystem or human assets (Varner et al., 2005).

These results point to a gap between ''knowing'' – conservation goals that aim to restore large extents of longleaf pine – and ''doing'' – implementing prescribed burning for restoration. Our results suggest that restoration is not the primary focus of burning in the longleaf pine ecosystem, despite the stated goal of large-scale restoration there. On one hand, the higher incidence of burning on sites that are already in good condition is an encouraging outcome because it suggests that high-quality sites are likely to be maintained under the current management regime. Conservation plans and researchers have stated that a focus on high-quality sites should be the first objective in longleaf conservation efforts because of benefits to species found on those sites (Van Lear et al., 2005; America's Longleaf, 2009). The majority of the 187 rare plant species native to the longleaf pine ecosystem will disappear without fire (Walker, 1993), and many threatened or endangered animal species, including the Red-cockaded Woodpecker, depend on the open midstory that results from frequent burning. Maintaining the good quality habitat that already exists is certainly critical for these species.

On the other hand, simply maintaining the sites already in good condition will not be enough to achieve sustainable populations of rare species. Less than 10% of the existing longleaf pine habitat in the Southeast is in a condition sufficient to support most of its native plant and animal species (Frost, 2006) and there are 16 federally threatened or endangered plant species associated with the longleaf pine ecosystem for which fire suppression is cited as a reason for listing (Van Lear et al., 2005). Restoring additional habitat by reintroducing fire into lower quality sites, especially in areas surrounding well-maintained sites will be essential (Hoctor et al., 2006).

The model that incorporated only non-ecological attributes suggests that several other factors besides ecological condition help determine the placement of prescribed burns. Statistical results for that model indicate an increased probability of burning at larger sites, those with a smaller proportion of previously unburned area, those that were farther from roads, those that were closer to other recent burns, and those that contained a smaller amount of managed timber. All of these factors are likely important in determining where burns are placed because they help avoid short-term damage that can result if a burn becomes out of control. Burning sites that had been burned in the past and conducting burns near recently burned sites can pose less risk if a fire becomes out of control. Those sites would have decreased fuel accumulation and firebreaks would already be established. Burning sites away from roads and without managed timber poses less short-term risk to human health, property, or investments.

Furthermore, in our analysis, sites that had not been burned for at least 4 years showed an increased probability of being burned as distance from development increased. In longleaf pine ecosystems, the time since a site was last burned is a proxy for understory and midstory fuel buildup. Our result was unexpected, and extends the results of previous research about the effect of the WUI on burning. Previous studies have emphasized limitations to burning in the WUI in longleaf pine and other ecosystems (Winter and Fried, 2000; Wade and Mobley, 2007; Taggart et al., 2009). While our results agree with these past studies, they emphasize that the influence of the WUI on burning depends on the condition of sites. The distinction shown in our results between recently and non-recently burned sites indicates that fuel build-up modifies the influence of the WUI on burning.

The ecological and non-ecological attributes associated with the placement of burns in the longleaf pine ecosystem point to a feedback in which currently degraded sites are less likely to be burned, and those sites will be more difficult to restore in the future, especially with future expansion of developed areas. Because proximity to development has the most influence on sites that have not been burned recently, as sites go longer without being burned, burning near development will become more difficult. That result, coupled with projections of increased development especially adjacent to protected areas (Wade and Theobald, 2009) means that in the future, the WUI will influence burning on a greater number of sites. The lower incidence of burning degraded sites now could negatively impact the longleaf pine ecosystem over the long term. Thus, our results suggest that when it comes to implementing prescribed burning for restoration of the longleaf pine ecosystem, the gap between knowing and doing may become wider in the future.

The model incorporating both non-ecological and ecological variables performed best overall, indicating that both ecological and non-ecological attributes of sites influenced whether they were burned. The model incorporating only non-ecological variables performed better than the model with ecological variables, in agreement with our hypothesis that non-ecological factors were more important in determining the placement of burns. The best model had an AUC of 0.73, indicating that it can correctly distinguish burned versus unburned areas approximately three-quarters of the time. These models incorporated meaningful spatial and temporal correlation. The pattern in the temporal correlation re-

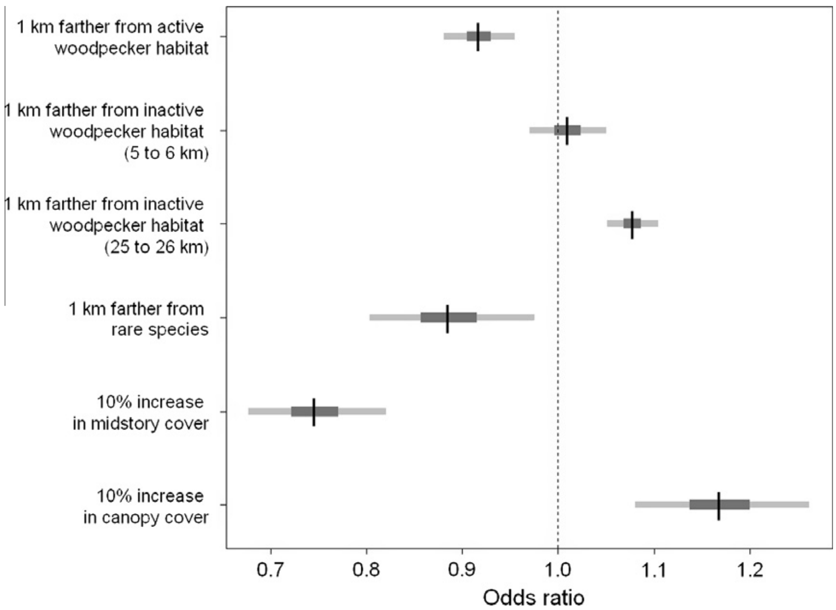

Fig. 2. Odds ratios for the model with ecological predictors only. Values above 1.0 indicate an increase in odds of burning with the stated change in the given variable; values below 1.0 indicate a decrease in odds of burning. Light gray bars indicate 95% confidence intervals. Dark gray bars indicate 50% confidence intervals. Distance from inactive Woodpecker habitat showed a quadratic relationship with burning; therefore, two distances are used here to illustrate the change in effect at different values of this predictor.

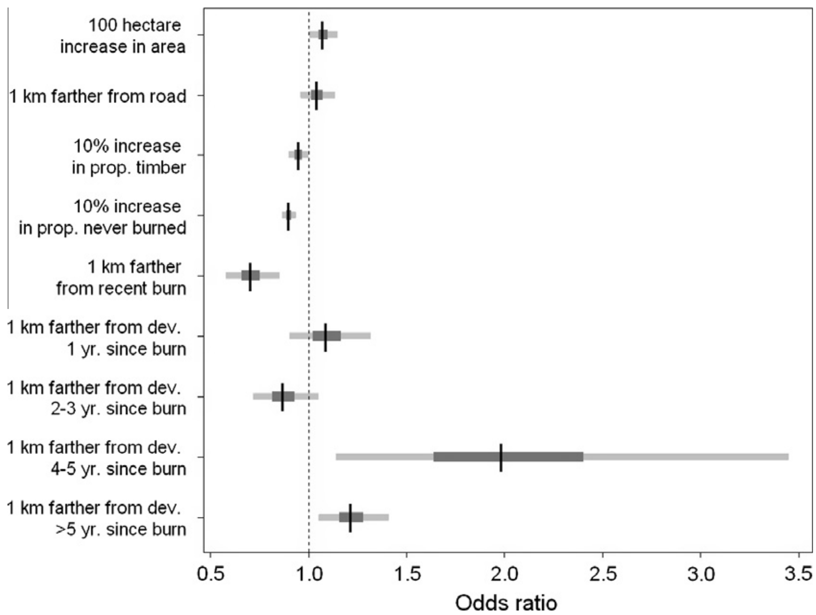

Fig. 3. Odds ratios for the model with non-ecological predictors only. Values above 1.0 indicate an increase in odds of burning with the stated change in the given variable; values below 1.0 indicate a decrease in odds of burning. Light gray bars indicate 95% confidence intervals. Dark gray bars indicate 50% confidence intervals.

flects a common rule-of-thumb for management of longleaf pine ecosystems of burning the same site every 3 years. The spatial pattern in the semivariograms reflects the fact that sites nearby are likely to be burned in the same year as well as 3 years later.

While we were not aiming to make a comprehensive model to predict prescribed burning, the models could be expanded. In particular, one set of predictors that is missing from this study relates to factors that constrain burning on a day-to-day basis. Limited resources, including personnel and equipment, and unsuitable weather conditions often constrain the amount of burning that can be conducted (Costanza and Moody, 2011). To further inform the strategies that could be implemented to achieve ecosystem restoration goals, these constraints could be incorporated into a more sophisticated modeling framework to project prescribed burning "opportunity", similar to the idea of mapping the opportunity associated with acquisition of land for conservation (Knight et al., 2010).

Scientific literature recommends the use of prescribed burning to restore fire-dependent ecosystems, and conservation organizations and government agencies are committed to restoration. Thus, finding ways to facilitate burning on sites in need of restoration will be critical for closing the knowing–doing gap. One way to facilitate burning on these sites is to reduce the uncertainty associated with burning outcomes by increasing scientific knowledge and accumulating of practical experience regarding effects of fire reintroduction. For example, recent studies of the effects of fire reintroduction into longleaf pine and ponderosa pine (*Pinus ponderosa*) forests suggest that increased tree mortality is linked to smoldering combustion of forest floor organic matter (Stephens and Finney, 2002; Varner et al., 2009). Determining the mechanisms behind this effect and the land management practices that would prevent such mortality would help managers refine their strategies for reintroducing burning. In addition, beginning by reintroducing fire into sites that are adjacent to recently burned sites and away from the WUI would help burn practitioners gain experience with fire reintroduction in sites with less risk to human health or property.

Finding ways to accept some uncertainty associated with burning would also help encourage restoration. While embracing uncertainty is a key tenet of adaptive management, management agencies often have difficulty accepting surprise in practice (Gunderson, 1999). A shift from a focus on "command and control" to recognizing the value of learning and experimentation within agencies would help encourage fire managers to take prudent risks when burning. One way to make this shift is by measuring a successful burning program not solely based on the total area burned annually, but also on the amount of burning successfully conducted on difficult sites. Implementing these strategies would help ensure that management activities can achieve conservation goals and reduce the knowing–doing gap in fire-dependent ecosystems.

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Supplementary material

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