Bayesian networks as a framework to step-down and support Strategic Habitat Conservation of data-poor species:

A case study with King Rail (*Rallus elegans*) in Eastern North Carolina and Southeastern Virginia

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EXECUTIVE SUMMARY

Although Bayesian network (BN) models have been promoted to the conservation community as models well-suited to support adaptive management strategies, there have been few tests of these claims. To test the value of BNs to support U.S. Fish and Wildlife Service and U.S. Geological Service's Strategic Habitat Conservation approach to adaptive management, we modeled habitat occupancy of breeding King Rail, Rallus elegans, in Eastern North Carolina and Southeastern Virginia. The limited regional empirical data for this species, combined with its priority conservation status, made it an ideal candidate to explore strengths and weaknesses of an expert-based Bayesian modeling approach. Specifically, we evaluated whether BN models initiated with expert knowledge and incrementally updated with empirical data could effectively support the definition of population and habitat objectives at regional and local (e.g., refuge) scales. Following two years of field surveys, we compared occupancy predictions from the original expert-only BN model, using a variety of BN models updated with different methods and with different data, and empirically-derived detection-adjusted occupancy estimates calculated in the program PRESENCE. To interpret differences among these models, we considered the relative contribution of spatial data error, expert error, and uncertainty to overall model error. Our results demonstrate how BN models can advance conservation for poorly documented species. We also provide recommendations to maximize the utility of expert knowledge within BNs designed to support the U.S Fish and Wildlife Service's and U.S. Geological Service's adaptive management processes.

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Chapter 2

AN EXPERT-BASED BAYESIAN NETWORK APPROACH TO MODEL HABITAT OCCUPANCY OF DATA-POOR SPECIES

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2.1 Introduction

Several publications offer guidance on the development of Bayesian network (BN) models for conservation and resource management applications (e.g., Kuhnert et al. 2010; Marcot et al. 2006; Varis and Kuikka 1999). All agree that model development must proceed from a clearly defined purpose. Our research goal was to step-down existing national and regional habitat models (e.g., Southeast Gap Analysis Program [SEGAP] models) to (1) inform land management and land acquisition decisions at the scale of management units within a National Wildlife Refuge (~20-400 ha; 50-1,000 ac) and (2) support learning through adaptive management and monitoring. Although the SEGAP models provide valuable information for national planning, the binary Potential Habitat/ versus Non-Habitat predictions are not designed to support refuge-scale planning. The quality of available potential habitat and the probability that a unit of potential habitat would be occupied by a King Rail during breeding season can vary greatly. Knowledge of this variability through space and time is critical for refuge managers who must prioritize management actions among many sites, all designated as potential habitat by SEGAP. Therefore, our first objective, addressed in this chapter, was to construct a BN model that would use available spatial data and expert knowledge to reclassify SEGAP potential habitat with higher precision and that would incorporate measures of uncertainty. Our BN generates spatially-explicit, probabilistic predictions of King Rail occupancy of potential habitat during the breeding season.

BN models consist of nodes (input, intermediate, and output nodes) linked in relationships through conditional probability tables (CPT) according to hypothesized causal relationships. Input nodes define states for predictor variables, in our case, landscape attributes, extracted from spatial datasets expected to serve as environmental correlates for King Rail breeding habitat occupancy. Intermediate nodes define how landscape attributes combine to predict suitability of potential habitat patches (i.e., set of contiguous raster grid cells of similar land cover type) and sites (e.g., individual raster grid cells) within patches. The output node reports the probability of occupancy by King Rail during the breeding season. We constructed the BN model based on information gathered through literature review and expert knowledge elicitation. We later updated and tested our model with locally collected field data (see Chapters 3 and 4).

We generally followed the guidelines of Marcot et al. (2006) for the development of alpha and beta level BNs. Biologists knowledgeable of local King Rail and their associated habitat (i.e., experts) identified and ranked possible environmental covariates of King Rail breeding season distribution patterns and also proposed causal mechanisms behind these correlations. Then in Netica (v4.08, Norsys Software Corp. 2008, www.norsys.com), we constructed an influence diagram to describe the system structure, defined node states, and defined probabilistic relationships among variables. The model structure and the underlying conditional probability tables drew upon the combined input of information gathered through the literature review and expert interviews, but were constrained by the availability of spatial data and were not constructed interactively with the experts in a workshop setting. Following construction of an alpha-level BN model, the experts had an opportunity to review and revise the model. The resulting beta-level model was used to generate habitat occupancy predictions.

In our model, raster grid cells attributed with the values of each covariate are the units for which responses are calculated. Although most raster data layers offered complete coverage of the study area, a few offered only partial coverage. However, tolerance of missing data is a strength of BN models (Uusitalo 2007). After generating occupancy predictions, we conducted two years of call-back surveys in the study region to calculate the empirical probability of occupancy and test the utility of the BN models as an adaptive monitoring and management tool (Marcot et al. 2006; Nyberg et al. 2006). A third year of call-back based occupancy estimates from another King Rail project in the same region (Rogers 2011) enabled us to complete a second round of model validation and to compare alternative habitat occupancy modeling strategies (see Chapter 3).

2.2 Methods

2.2.1 Literature Review

We began our literature search using library databases available through North Carolina State University library system (http://www.lib.ncsu.edu/databases/) for all publications mentioning King Rail (or *Rallus elegans*) at any point in the text, including peer-reviewed science literature (Web of Science; ProQuest Biological Sciences; Wildlife and Ecology Studies Worldwide; Google Scholar), theses and dissertations (ProQuest Dissertations & Theses), and government published gray literature (Google). We also searched the USGS Publications Warehouse (http://pubs.er.usgs.gov/) and the USFWS Conservation Library (http://library.fws.gov/Publications.html). The literature cited section of each publication was cross-checked against publications obtained through database searches to ensure inclusion of all available literature. Every publication was entered into the avian habitat and vital rates literature review tool, Lit Review Central (E. Laurent, developer). This tool facilitated documentation and summary of both qualitative and quantitative habitat associations. Information obtained through the literature review guided development of the expert elicitation process; all landscape or microhabitat associations identified in the literature were presented for experts' consideration.

2.2.2 Expert Knowledge Elicitation

Different elicitation methods generate different information and biases from individual experts. We conducted two elicitation procedures to compare responses of individuals across methods (expert consistency) and to evaluate which method supported greater predictive accuracy. The first procedure focused on a series of questions discussed in an informal one-on-one interview, while the second required experts to classify the probability of King Rail detections at points placed upon aerial imagery. We here report methods and results based on the interview method, which required less effort and offered stronger predictive performance. Methods and results from the comparative study are published separately (Drew and Collazo 2011).

Expert interviews elicited local biologists' hypotheses regarding King Rail response to landscape and microhabitat environmental gradients within the Ecoregion (Drew and Collazo 2011; Kuhnert et al 2010; Marcot et al. 2006). Before our field research, King Rail had never been studied in the Ecoregion, so only five individuals could be located to offer knowledge of King Rail habitat associations within the ecoregion. Thus the available King Rail expertise was low (as per Perera et al. 2012), with narrow scope and emphasis on microhabitat detail. However, our experts' knowledge and expertise regarding waterbird ecology generally was high (as per Perera et al. 2012); experts demonstrated awareness of the system's variability and were able to evaluate patterns across scales to propose mechanistic hypotheses. Four of the five participating experts were USFWS biologists serving at local refuges and the fifth was a contract ornithologist who regularly surveyed King Rail as part of regional bird population monitoring (Figure 2.1). The USFWS experts offered a long history of experience within the marsh habitats on their refuge lands, but could not necessarily comment on whether their observations applied more broadly to marshes on neighboring federal, state, or private lands. The contract ornithologist had broader familiarity with regional marsh landscapes, but rarely ventured off trail or roadside in the course of his surveys. Although none had formally researched King Rail populations, all monitored avian populations and maintained avian habitat as part of their work and all had observed King Rail in the course of their work.

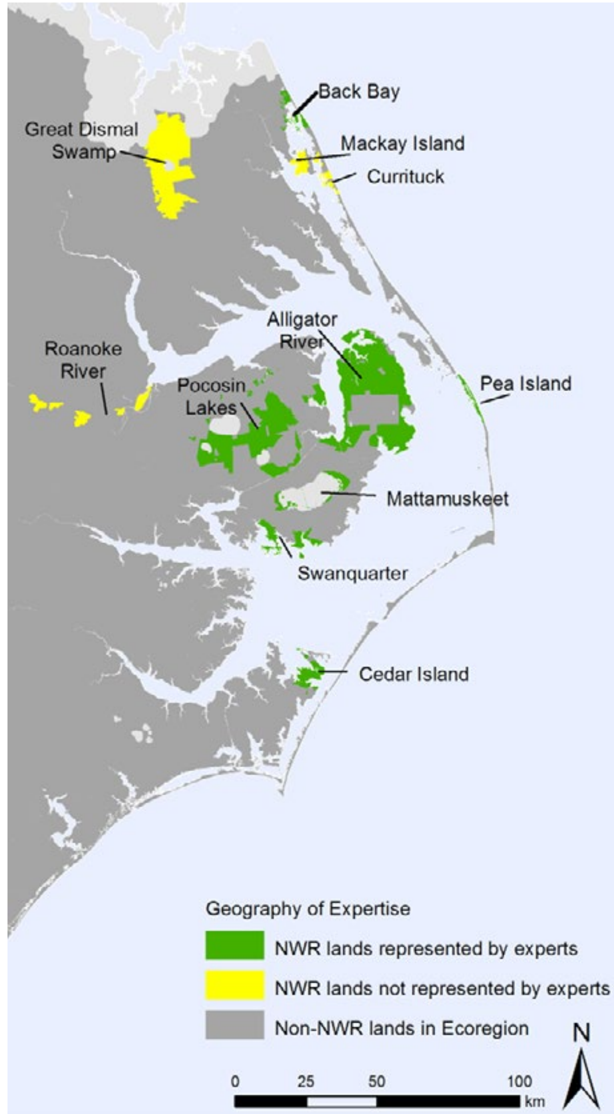


Figure 2.1. Geography of expertise. Locations of 11 National Wildlife Refuges (NWR) within Eastern North Carolina and Southeastern Virginia, distinguishing between those refuges represented (green) and those not represented (yellow) by experts.

We interviewed each expert privately at their own office. The interview followed a semi-structured approach and was presented in two parts over a period of approximately 3 hours. We prepared a script (Appendix 2.1) to ensure that all experts received the same orientation and that all elicitations followed the same procedure. We documented experts' responses as they answered, allowing them to review our summary interpretation of their knowledge. Audio recordings of the interviews enabled review of elicited information during model construction.

Part One of the interview sought to characterize the domain and foundation of each expert's knowledge (Drew et al. 2012). The questions gathered information to define: (1) the spatial and temporal extent and resolution of the experts' relevant work experience; (2) the knowledge resources (e.g., personal observation, literature, colleagues) that shaped their professional judgments; (3) their familiarity with reading digital orthophotos that would be referenced during elicitation; (4) their self-confidence in their knowledge of King Rail habitat occupancy; and (5) their overall belief that King Rail habitat occupancy is at least partially driven by landscape-scale habitat patterns identifiable in remotely-sensed spatial data. The information gathered in Part One could be used to evaluate or weight experts' knowledge and also allowed time to orient the expert to the interview method, geographic scope, and vocabulary (Kuhnert et al. 2010; O'Hagan et al. 2006; Renooij 2001).

In Part Two, experts first identified landscape and microhabitat variables of potential importance, then directly quantified relationships between King Rail distribution patterns and each variable (Marcot et al. 2006). Experts were directed to consider two processes: the probability of a King Rail locating a patch of marsh habitat and the probability of finding a suitable site to establish a nest within that patch. After first brainstorming their own list of variables, if an expert failed to independently identify a specific variable mentioned in the literature or by another expert, these missing variables were added to their list. The relationships between each variable and King Rail habitat occupancy during the breeding season were defined based upon the expected number of sites that would yield at least one King Rail detection during ten spatially replicated call-back surveys (Conway 2008a) for a given value of the target variable. They were then asked to estimate the proportion of King Rails present that they thought would typically be detected by this survey method. Although not all experts agreed with the appropriateness of the standardized call-back survey protocols, they were constrained to answer based on this method because this would be the method used to collect empirical data to validate the model.

When answering, we instructed experts to assume: (1) that these hypothetical surveys were conducted under conditions that would maximize detection probability for this species (e.g., during the peak of breeding season, under ideal sampling conditions), and (2) a near perfect correlation between occupancy and detection probabilities. For each microhabitat and landscape variable, experts identified a minimum or maximum value threshold beyond which the expected probability of detection would drop to zero (e.g., limiting variable). If an expert expected the variable to be compensatory rather than limiting, the expert specified a value or range of values that would offer minimum probability of detections. Then the expert identified the variable value or range of values that would offer maximum probability of detections (i.e., mode). Once experts had identified these points along the variable axis (x-axis), they then predicted detection probabilities for these extreme and central points and, if possible, additional intermediate points. Finally, to facilitate comparison among experts' responses, experts identified what they considered the highest possible detection probability and the proportion of the population detected relative to the proportion present under ideal conditions on their refuge. In all steps, experts were asked to explain the reasoning behind their hypotheses. After full discussion of all variables, experts were asked to identify the five, and then the two variables most likely to influence King Rail distribution throughout their own refuge. We assigned scores to the variables within these sets; variables in the set of two were considered to have a High predictive and explanatory value (score = 2), while the remaining three selected variables were ranked of Moderate value (score = 1). All unselected variables received a score of zero. After eliciting knowledge from all experts, we summed the scores from all five experts to obtain a ranked list of variables as defined by expert knowledge.

2.2.3 Spatial Data Selection and Preparation

To generate landscape scale predictions in support of refuge-level decisions, the BN model required spatial data available at the full extent of the study region but of fine enough resolution to discern habitat differences within refuges. Available data were the SEGAP land cover and ancillary data layers (e.g., roads) and the National Hydrological Data (NHD) (USGS and USEPA 2005). Each variable proposed by the experts was carefully considered and, if possible, matched to a landscape metric that would serve as a proxy for the expert-defined pattern or process. Variables that could not be reasonably approximated with landscape metrics were not incorporated into the BN model.

Any errors or uncertainties in the spatial data – as with all other inputs and causal relationships represented in the model - would be propagated through the BN. Assessment of the SEGAP marsh classification prior to modeling yielded three possible cover classification problems that may have strongly impacted conclusions drawn from our BN models. The first problem was related to the scale of the data. SEGAP provided a coarse depiction of marsh land cover that fails to represent the many small channels and ponds scattered throughout the marsh landscape, and therefore potentially overestimates total vegetated marsh area and underestimates the amount of marsh-water edge. Therefore, we reclassified as water any marsh grid cells positioned underneath linear water features (e.g., creeks and ditches) depicted within the NHD. One result of this change was a lower estimate of available breeding habitat, as the classification error would shift from a possible over-estimate of marsh cover to a possible over-estimate of water cover.

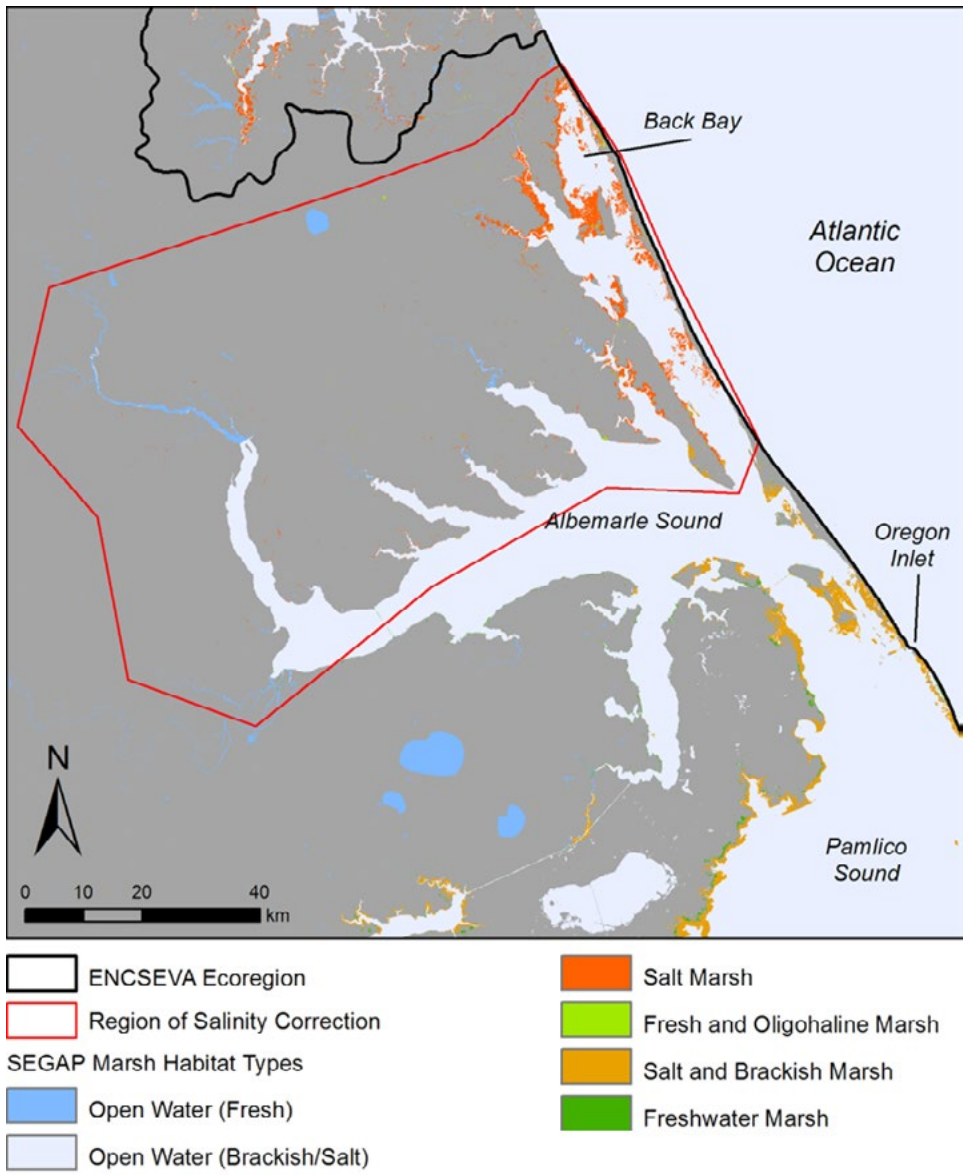


Figure 2.2. Salinity correction within the Eastern North Carolina and Southeast Virginia (ENCSEVA) Ecoregion. Distribution of marsh land cover classes in Southeast Gap Analysis Program (SEGAP) data. The region north of the Albemarle Sound (red polygon) was incorrectly mapped as Salt Marsh in SEGAP and was corrected before modeling King Rail habitat for this project.

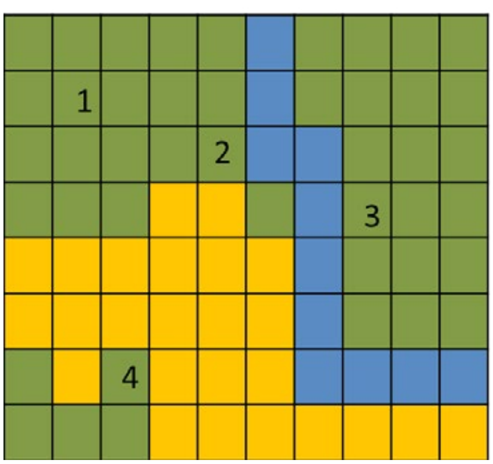
The second and third problems related to possible cover classification errors. One region, Back Bay, had been incorrectly mapped as salt marsh habitat, when in fact this area is an unusual fresh-oligohaline coastal embayment (Figure 2.2; USFWS 2010; USFWS 2008a). In fact, the entire Albemarle Sound is an oligohaline system with salinities rarely exceeding 5 ppt (Garrett 1993 ; Copeland et al. 1983). We manually reclassified this region as fresh-oligohaline marsh habitat (Figure 2.2), a decision later affirmed by salinity and vegetation data collected in the field (salinities less than 5 ppt; vegetation dominated by freshwater emergent vegetation including cattail [*Typha* spp.], cordgrass [*Spartina* spp.], bulrush [*Scirpus* spp.], and rosemallow [*Hibiscus moescheutos*]). We also noted that SEGAP mapped as water the 8.3 km^2 of fresh marsh at the southern edge of Lake Mattamuskeet in Mattamuskeet National Wildlife Refuge, a marsh known to support breeding King Rail (USFWS 2008b). This marsh habitat was not reclassified, because we decided that it was likely not a misclassification error. Rather, the water classification likely reflected the true state of this marsh during capture of the winter aerial imagery used to classify land cover. We confirmed that this marsh is impounded marsh habitat that typically is flooded for winter waterfowl (J. Stanton, USFWS, personal communication).

Once the spatial data had been fully evaluated and corrected, each raster grid cell (30-m grain, matched to the resolution of SEGAP) was assigned a unique identification number and attributed with the values of the selected variables. We performed all spatial data processing in ArcGIS 9.3. We exported the final attribute data of all grid cells as a text file for input as cases within Netica. Importantly, this meant that although the model generated spatially-explicit prediction, these predictions were generated in an aspatial statistical framework; we did not incorporate metrics of spatial autocorrelation among raster grid cells.

2.2.4 Structure and Construction of the Bayesian Network Model

BN structure must reflect ecological processes relevant to the scale of model objectives. Our model predicts King Rail breeding season occupancy based on spatial information at two scales: (1) marsh patches (range: 0.09 to 2,422 ha, median 104 ha, $\bar{X}$ = 376 ha, SD = 555 ha) within the Ecoregion, and (2) sites (i.e., 30-m raster grid cells, 0.09 ha) within individual marsh patches (Figure 2.3). These spatial scales move beyond simple questions of species-habitat correlation by

Figure 2.3. Marsh patch and site scales. A simplified representation of the raster data format with an example of the associated patch- and site-level metrics (for full list and definitions, see Table 2.4). In this illustration, green grid cells are marsh, yellow grid cells are forest, and blue grid cells are water. Every raster cell is attributed with data corresponding to each input node in the BN model. The BN model then generates a predicted probability of occupancy by King Rail during the breeding season for each raster grid cell based on the attributed data.



	Raster Grid Cell			
	1	2	3	4
Patch-level Attributes				
SIZE	19	19	20	5
TYPE	Edge	Edge	Edge	Interior
Site-level Attributes				
WATER	Far	Near	Near	Far
COVER	Marsh/Water	Marsh/Water	Marsh/Water	Forest

requiring consideration of two processes that influence habitat occupancy: access and selection (Jones 2001). We characterized access as acting primarily at a marsh patch level and characterized breeding territory selection as a site level process. We asked experts if and how patch characteristics, such as location, size, and connectivity, influence the probability of a King Rail accessing the patch during its search for breeding habitat. We then asked experts if and how a King Rail's decision to remain and establish a breeding territory within a given patch would reflect available resources (e.g., for nesting and foraging) within the patch and the threat of anthropogenic disturbance (e.g., watercraft, roads). Thus, in our models, the probability of King Rail occupancy varied among and within patches. We excluded consideration of biotic factors (e.g., presence of predators, competitors, or potential mates) that also influence selection processes. As a result, our predictions of occupancy could be biased towards higher values than would be found in the field.

Netica requires that all variables be represented as state variables or constants (Uusitalo 2007). We directly elicited experts' knowledge regarding potential thresholds or response curves as affecting King Rail occupancy for each variable they named. However, in many cases, their knowledge was inadequate to propose details beyond a positive, negative, or neutral response. In such cases, we defined the categories for state variables based on our literature review. If that failed to reveal relevant information, we defined categories based on the range of values within the Ecoregion. For example, in the absence of any ecological information to define categories for a two-state variable, we used the median to distinguish between High and Low value bins. It is important to note that this division has no known ecological meaning. Rather it serves to ensure that when the model is used to establish sampling strata for later monitoring efforts, that surveys are evenly dispersed across the range of habitat conditions for that variable to maximize learning. By this means, the data necessary to establish ecologically relevant thresholds should gradually be obtained.

Construction of the influence diagram and conditional probability tables sometimes required reconciliation of experts' individual probability estimates. One approach to address differences among experts' probability estimates is to simply average responses of all experts or to weight experts by their years of experience. However, we had noted in our interviews that experts differed not only in years of experience, but also in their exposure to, and thus expertise regarding, different habitat conditions. For example, some experts experienced landscapes with high variability in salinity but minimal variability in patch size, while others experienced marsh habitat of all sizes but only a very narrow range of salinity. Furthermore, in many cases, although experts disagreed regarding the probability of occupancy for a given landscape value (e.g., patch of a given size), they generally agreed about the relative change in probability of occupancy across the full range of values (e.g., from smallest to largest patch size in the landscape). Therefore, we evaluated differences among experts in light of: (1) experts' stated maximum detection probability (e.g., experts could disagree on an absolute scale while agreeing on a relative scale); (2) the range of conditions represented within an expert's refuge (e.g., distinguishing responses based on local observation versus extrapolation); and (3) experts' relative experience (e.g., years at refuge, time spent in marshes during breeding season, and number of King Rail sightings). Wherever differences were determined to be simply differences regarding strength of response rather than shape of response curve, we combined experts' responses by assigning the greatest weight to the expert having the most knowledge for a given variable, rather than simply defaulting to weight responses by an expert's years of experience. Where differences could not be explained reasonably and reconciled through such comparisons, we conducted follow-up conversations or allowed evidence from the literature to guide our development of the alpha level BN. All experts reviewed the preliminary alpha-level model and recommended adjustments bfore approving the beta-level BN that we applied to the Ecoregional landscape.

2.2.5 Verification of the Model Structure

Model verification is a process whereby the model structure is checked to ensure that it has accurately incorporated and documented the available knowledge. In an expert-based model, this primarily entails reviewing the model with the original experts to ensure it accurately represents their knowledge and expectations. Model attributes that must be checked are the list of variables, the rank of variables, and the relationships (structural and probabilistic) among variables. Much of this is simply visual inspection, but we also used Netica's sensitivity analysis. This tool uses entropy reduction (for categorical target variables) and variance reduction (for continuous target variables) (Marcot et al. 2006) to report how much the mean value of the target variable (here, probability of King Rail occupancy) varies based on a change in the input value for each predictor variable in turn. We compared the ranks of the variance reduction values for each variable as represented within the BN, to the ranked scores of the same variables as elicited directly from the experts. Differences between the two rankings indicated either inconsistencies between experts' stated knowledge and the model representation of their stated knowledge or the presence of complex interactions among variables captured more accurately by the BN structure than by experts' rankings of individual variables. We used this comparison as a communication tool to evaluate and, if necessary, adjust the model to better match experts' hypotheses. It is important to note that model verification does not provide any information regarding the predictive accuracy or precision of the model, which is addressed below.

2.2.6 Spatially-Explicit Occupancy Predictions

A text file exported from ArcGIS contained 1,002,983 records representing the individual raster grid cells with their attributed variable values. We processed these records as cases through Netica and then returned them to ArcGIS for visualization. The Netica output reported the expected value for the probability of occupancy (E[KIRA]), the standard deviation of the expected value, the most likely occupancy category (Low, Moderate, or High), and the probability of each occupancy category. In addition, it was possible to specify reporting of summary statistics for any intermediate node within the BN model. We chose to report summary statistics for the primary mechanisms, patch access and nest site selection, to facilitate understanding whether one or the other was limiting at sites predicted to have low occupancy.

It is important to note that the probability of occupancy calculated by Netica, referred to as the expected value, is not the value most likely to occur. Rather it is the mean value that will occur, where the mean is weighted by the probability of occurrence associated with each category (Netica Help documentation). For example if the value will be Low (between 0 and 0.33) with probability of 0.923, Moderate (between 0.34 and 0.66) with probability 0.0655, and High (between 0.67 and

1.0) with probability of 0.0116 then the expected value for the probability of occupancy is: (0.923 * 0.165) + (0.0655 * 0.495)+ (0.0116 *0.825) = 0.194. The standard deviation is calculated as:

$$\int_{-\infty}^{\infty} (x-\mu)^2 p(x)dx$$

where μ is the mean value (i.e., expected value).

2.2.7 Validation of the Model Predictions

The process of model validation assesses the ability of the model to explain or predict real-world observations. In 2008 and 2009, we surveyed 105 potential habitat marsh sites using the National Marsh Bird Survey Protocol (Conway 2009; Conway 2008a). The sites represented a stratified random sample (see Chapter 3 for design details), with strata selected to represent the network variables that contributed most to uncertainty in the model predictions (patch size, distance to open water, and dominant land cover).

We surveyed each site three times for King Rail response and microhabitat characteristics. We then estimated the probability of occupancy given detection history using PRESENCE software (see Chapter 3 for statistical details of model construction and selection). PRESENCE estimate detection probability ($\hat{p}$) and probability of occupancy ($\hat{\Psi}$) conditional on detection. After accounting for year and sampling period effects on detection probability, we combined all 2008 and 2009 field data for analysis (see Chapter 3 for description of methods and assumptions). We performed five analyses in PRESENCE (see Chapters 3 and 4), all as single-species, single-season models with heterogeneous detection probability (MacKenzie et al. 2006). Our PRESENCE occupancy models incorporated the SEGAP potential habitat designation, landscape data, and microhabitat data, alone and in combination, to explain observed occupancy patterns. The top model from these analyses provided the occupancy estimates used in the validation procedures.

We validated the model by comparing the occupancy predicted by the network with the detection-adjusted occupancy estimates. We conducted two tests. A pair-wise t-test (two-tailed, alpha = 0.05) tested the null hypothesis of equality of the two data sets. The Test-with-Cases function in Netica calculates statistics in an error matrix, reporting overall percentage error. With this function, we explored whether errors of commission or omission are more common.

2.3 Results

2.3.1 Literature Review

We identified and reviewed 275 papers published between 1835 and 2006 (Table 2.1) that offered primary results (not a summary of previously published results) regarding King Rail in North America. We documented all comments and data that associated King Rail observations with habitat characteristics (Appendix 2.2). Although particularly interested in landscape-scale habitat characteristics (e.g., direct reference to mapped land cover classes or features), we also documented all references to microhabitat characteristics. The best documented habitat features were

Table 2.1. Literature review results. Of 275 publications (1800s to 2006) mentioning King Rail in the text or title, most did not provide information useful for developing spatially-explicit, landscape-scale species-habitat models.

Publication Category	Category Description	Number of Articles
Quantitative mappable data	Publications provide a date, location, measured landscape or landcover variable, and response in terms of abundance, density, or productivity	13
Qualitative mappable data	Publications provide an observation in terms of presence, abundance, density, or productivity, with text description of associated habitat	88
Comments without mappable data	Literature reviews, most atlas or breeding birds summary reports, and publications where the location or habitat type was not mentioned in association with bird observations	48
Not relevant	King Rail were not mentioned in the text (often true where a King Rail publication was cited in references), study was outside the geographic region of interest (North America), or study had no relevance to species-habitat associations (e.g., study on origin of species' common names, paleontology studies, geographic location rather than habitat type noted)	126

vegetation species, water depth, distance to road, distance from marsh-water edge, and wetland area (Appendix 2.2). Wetland area measurements, however, typically failed to indicate if the estimate reflected administrative or natural boundaries, and whether the total area included marsh vegetation only or also open water. Most publications provided no information directly relevant to modeling breeding season habitat associations at Ecoregional scales (Table 2.1).

2.3.2 Expert Knowledge Elicitation

2.3.2.1 Expert Knowledge Metadata

The five participating experts (Table 2.2) had significant experience working in marsh bird habitats generally (12 to 38 years) and the local refuges specifically (7 to 16 years). Their knowledge was drawn from diverse sources, but all included personal observation (visual and/or auditory) of King Rail in the course of their work duties. After discussing the project's immediate objectives (e.g., to develop landscape-scale models of King Rail occupancy) and examples of landscape-scale variables (e.g., patch size, distance to roads), the experts ranged from neutral to confident that King Rail distribution patterns correlate with patterns in the landscape data. Most experts (4 of 5) were slightly less confident that they would be able to identify the landscape or microhabitat variables most strongly correlated with landscape-scale distribution patterns. All experts recognized that their observations of King Rail, and their associated mental models of King Rail habitat associations, were potentially affected by the low probability of detecting the birds even when present. They estimated that detection rate might vary from 30 to 75% using Conway (2008) standardized

Table 2.2. Summary of available expertise. Some of the data collected to document the five experts' domains of expertise included: years of experience reported by geography, knowledge resources, and metrics to characterize their confidence in the proposed modeling and monitoring process.

Expert Name	National Wildlife Refuge (s) in the Eastern North Carolina and Southeastern Virginia Ecoregion where you have worked	Experience in Marsh Bird Habitats (years): North America	Atlantic Coastal Plain	ENCSEVA	Your Refuge (s)	Primary Knowledge Resources	Landscape (mapped GIS data) patterns influence KIRA distribution patterns (0 = strongly disagree, 5 = neutral, 10 = strongly agree)	I can identify relevant habitat (landscape and microhabitat) variables (0 = strongly disagree, 5 = neutral, 10 = strongly agree)	Estimate of Detectability by Call-back Method
J. Stanton	Cedar Island; Swanquarter; Mattamuskeet	20, mostly in fresh and brackish marshes; early career in Gulf and Great Basin (CA, NV)	15	12.5	7.5, split among these refuges, then migratory birds manager	Mostly from literature. Collected miscellaneous KIRA articles over past 15 years. Occasional Google searches (approx. 12- 1 hr sessions). Personal observation.	8/10	6/10	60 to 75%
W. Stanton	Pocosin Lakes; Pea Island	12, mostly focused on waterfowl in moist soil units and emergent wetlands	12	12	9, 3 years at Pea Island and then at Pocosin Lakes	Field guides. Participated in three secretive marsh bird call-back surveys at Pocosin Lakes as part of survey protocol development. Dialog with other biologists. Personal observation.	10/10	7/10	60%
J. Gallegos	Back Bay	32, significant portion in salt marshes with Clapper Rail (NJ), but KIRA habitat in VT and VA	25	16	16	Assisted with development and testing of secretive marsh bird call-back survey methods (approx. 10 years). Direct observation of KIRA in refuge marshes.	10/10	8/10	30 to 40%
D. Stewart	Alligator River	25, all in NC, including work with Black Rail in Hobucken Marshes	25	25	13.5	Field guides and one call-back paper from the refuge region. Personal observation.	5/10	7/10	Max 50%
R. Ake	Back Bay, MacKay, Alligator, Mattamuskeet, Pea Island, Swanquarter	38, 35 years as recreational and contractor ornithologist for bird surveys; sees 6-12 KIRA per year	35	35	N/A, but 7 years as contractor for marsh bird surveys at Back Bay	Personal observation and field guides. Data collection for marsh bird survey protocol development.	8/10	5/10	30 to 40%

call-back methods and that variable detection probability could cause them to miss or misidentify some important species-habitat associations.

2.3.2.2 Expert Variable Identification and Ranking

In total, the experts collectively identified 16 physical habitat variables: seven microhabitat and nine landscape variables (Table 2.3). Although not the focus of our elicitation, experts also noted the potentially strong influence of habitat management activity (e.g., regular disturbance to maintain healthy marsh) and the biological community (e.g., presence of suitable prey populations). At least one expert ranked each of the following variables to have the highest predictive and explanatory value for a model predicting King Rail occupancy: vegetation composition, water depth, marsh patch size, and salinity (Table 2.3). However, when we assigned scores to the ranks (rank High = 2

Table 2.3. Variables identified through literature review and by experts. Some expert comments are noted in the General Description column. Following discussion of all variables, experts identified those they believed to best predict King Rail occupancy. Experts' votes are indicated as the Rank Value of Information: High (H) and Moderate (M), based on whether they would rank it in the top three or the top five for information value, respectively. The score is the sum of all votes where a vote of High = 2,Moderate = 1, and no vote = 0. A Rank Score of zero does not indicate that experts hypothesized the variable to have no information value for predicting King Rail occupancy, but rather they would not expect it to be competitive among this set of potential model parameters. The final two columns indicate the microhabitat and landscape parameters defined to represent expert variables. These parameters are quantitatively defined in Table 2.4.

Variables Discussed	General Description	Experts (Rank Value of Information)	Final Expert Rank (Score)	Micro-habitat	Land-scape
Vegetation composition	Maybe avoids *Phragmites*? Observed in cattail, 3-square, flat sedge, and smartweed. Usually 3-5 species, in mix of annual and perennial, rather than mono-specific marsh. Diverse vegetation is best.	JS(H), JG(H), WS(H)	1 (6)	rich phrag	NDVI[1]
Water depth	Must at least be saturated soil, 6 inches depth probably ideal (0 to 12 inch range); or simply not deeper than a threshold (24 inch). They will swim across ditches.	JS(H), RA(H), WS(H)	1 (6)	depthX	na
Marsh patch size	Will nest in very small patches (min 1-2 acres; 10 acres) and probably no maximum size, though marsh diversity may decrease in large marshes. 50-100 acres (25-100 acres; 100-400 acres) hypothesized as best. Small heterogeneous patches, such as canal edges, can offer suitable habitat. If not a large patch, high connectivity would be beneficial.	JG(H), RA(H), WS(M)	2 (5)	na	SIZE CONNECT
Percent woody vegetation	Would avoid dense or tall woody cover where prey species (aquatic invertebrates) are less abundant. But *Hibiscus* and other shrubs are often present in preferred marshes. Should be < 30% woody cover.	DS(M), RA(M), WS(M)	3 (3)	woody shrub	na
Distance to open water	May require open water, best within 100 feet, but can be in very small patches (1 square foot). Standing or flowing water fine. Or absence of open water but with presence of permanently flooded vegetation may be preferable.	JS(M), DS(M), RA(M)	3 (3)	na	WATER
Amount of marsh/water edge	Natural and anthropogenic channels bisecting marsh habitat create ideal foraging edges. More likely to be found near edges than in interior, but this could reflect sampling bias.	JS(M), JG(M), WS(M)	3 (3)	edge	EDGE TYPE
Vegetation density	Dense vegetation is best so long as interspersed with some bare and some open water areas.	JS(M), JG(M)	4 (2)	na	na
Salinity*	Prefer fresh and brackish – not present in salt marsh (> 15 ppt is Clapper Rail habitat). Not confident that variability in salinity below 15 ppt would matter.	DS(H)	4 (2)	saltX	SALT

* The salinity value led to some confusion. All experts agreed that Clapper Rail, not King Rail, inhabit salt marshes, such that salinity (fresh, brackish or salt marsh) has a very high predictive value. However, when ranking the variables, only one expert (DS) ranked salinity high, due to other experts (JG, JS, WS, and RA) considering the value of salinity data within the fresh to brackish range. These four experts felt that King Rail were equally likely inhabit marshes across the gradient from 0 to 15 ppt. When, in model review, experts were presented with salinity as a categorical variable (Salt, Brackish, Fresh-Oligohaline), all agreed that it should rank high and these scores were modified n the BBN.

[1] Normalized Difference Vegetation Index, a metric used to classify vegetation in remotely sensed imagery.

Table 2.3, continued.

Variables Discussed	General Description	Experts (Rank Value of Information)	Final Expert Rank (Score)	Micro-habitat	Land-scape
Marsh patch context	Probably not that important, especially if patch large enough to support territory, except as contributes to likely sources of disturbance, invasive exotic species, and predators. KIRA might cross narrow forest or agricultural cover when foraging. Observed in ditches along busy roads and in agriculture fields.	JG(M), DS(M)	4 (2)	na	COVER
Distance to roads	Direct disturbance would deter KIRA from selecting a site for nesting (e.g. people walking or kayaking through marsh), but they seem tolerant of traffic. Dirt roads along ditches are regularly crossed, so open terrain does not seem a concern.	DS(M)	5 (1)	na	ROADS
Presence of boat traffic	Boat traffic is minimal near most marsh habitat, but presence of kayakers or wake from motorized watercraft could cause KIRA to avoid preferred edge forage habitat.	DS(M)	5 (1)	na	BOATS
Tidal/Non-tidal/Impounded	Measured in inches and strongly wind-influenced in this region, so not likely predictable influence. All known marshes with King Rail are mapped as tidal.	BA(M)	5 (1)	na	na
Soil type	Crayfish, a preferred food resource, are found in organic soils. Peat organic soils would be too acidic though. Mineral soils might be good, if they support suitable prey community. Soils and vegetation correlated.	JS(M)	5 (1)	na	na
Vegetation height	Diverse vertical structure achieved through mix of annual and perennial vegetation. Avoid very low, open "sedge meadow" vegetation except to cross through.	none	6 (0)	na	na
Elevation heterogeneity	Muskrats (but not nutria?) create "hummocky" elevation patterns associated with KIRA, but not necessary.	none	6 (0)	depthSD	na
Area of open water	Interspersion of marsh and water is important; not too much open water. Overwash by waves along exposed shorelines probably reduces the value of shorelines near very large open water areas.	none	6 (0)	na	FETCH
History	Documented past presence of King Rail is Breeding Bird Survey, Christmas Bird Count, or Natural Heritage Program Element Occurrence data.	none	6 (0)	na	HIST

points; rank Moderate = 1 point) and calculated the summed score for each variable, the following variables received the highest combined scores: vegetation composition (6), water depth (6), marsh patch size (5), percent woody vegetation (3), distance to open water (3), and amount of marsh/water edge (3) (Table 2.3). Variable ranks do not directly inform BN model structure, but can serve to check consistency between the final BN conditional probability tables and experts' expectations.

Variables not identified by experts, but discussed during the interviews, were landscape connectivity (the number of and proximity to neighboring marsh patches) and history (the documented presence of breeding King Rail in the past). Experts agreed that both variables might be informative and should be included, but neither variable ranked higher than those named above.

2.3.2.3 Thematic Organization of Variables

We organized the variables into two thematic groups based on habitat selection mechanisms proposed by experts during the elicitations. The first group contained variables that the experts thought to primarily influence the probability of accessing a patch. The second contained those judged by experts as more likely to influence the probability of selecting a site to establish a breeding territory.

Every expert described the probability of encountering a patch as a function of the marsh habitat's size and location in the landscape. Every expert hypothesized that dispersing King Rail would be more likely to encounter large patches that were near open water ways (rivers and embayments), and adjacent to other patches, than to encounter small patches that were isolated from neighboring patches or from open water. Given continued presence of healthy marsh habitat, the historical presence of breeding King Rails was also seen by every expert as increasing the likelihood of a patch being occupied in the present and future.

All experts described the probability of selecting a site and establishing a breeding territory as a function of the presence of suitable foraging habitat, suitable nesting habitat, and the absence of disturbance. Different experts emphasized different characteristics of marsh habitat during their elicitations. The following three views were initially expressed by just one or few experts and then approved by all during review of the preliminary model. First, experts hypothesized that marsh-open water edge habitat offered the best foraging opportunities, if the edge was not exposed to high wave energy. They also expected edge habitat to influence King Rail nest site selection. Experts hypothesized that King Rail would avoid both the immediate edge and the deep interior of a marsh, instead preferring an intermediate distance from open water that would provide access to the shelter of interior vegetation and the forage habitat of the water's edge. Second, experts further hypothesized that the vegetation at the site should be a heterogeneous mix of fresh- oligohaline (or brackish) annual and perennial emergent marsh species, rather than a monotypic stand. Salt marshes were deemed unsuitable to breeding King Rails (possibly due to unique characteristics of salt marsh vegetation, prey community, or presence of Clapper Rails). Finally, disturbance was the third mechanism described in relation to site selection for reproduction. Experts hypothesized that frequent traffic (vehicles on roads or boat traffic on waterways) could cause King Rails to relocate from otherwise suitable habitat to neighboring suitable habitat. However, they ranked the value of this information very low relative to other variables. They hypothesized that surrounding land cover context of a marsh patch (e.g., marsh, forest, agriculture, urban landscape) could influence the probability of disturbance by humans, invasive species, and some potential predators, but were uncertain how the non-marsh contexts would rank relative to each other.

2.3.3 Spatial Data Selection and Preparation

Twelve of the 16 variables identified could be directly or indirectly (via proxy variables) matched to the available GIS data (Table 2.4; see Chapter 5 for discussion of GIS data quality and concerns about proxy data selection). Variables matched directly to available spatial data were: salinity (*SALT*), distance to open water (*WATER*), presence of an open water edge (*TYPE*), amount of marsh water edge (*EDGE*), marsh patch context (*COVER*), distance to roads (*ROADS*), marsh patch size (*SIZE*), connectivity with neighboring patches (*CONNECT*), and historical presence (*HIST*). Variables requiring additional inference and the use of proxy data were: vegetation composition (*NDVI*), shoreline exposure related to area of open water (*FETCH*), and boat traffic (*BOATS*).

Of the variables identified, six were mapped as categorical (*TYPE, HIST, FETCH, SALT, COVER, BOATS*) values. However, the other six variables were mapped as continuous data and we defined the states for these variables. In the interviews, experts had been asked to provide hypothesized response curves for all continuous variables, but were only able to do so for four of the six variables (*SIZE, ROADS, WATER, CONNECT*). We used these discussions to define the variable states. We defined states for the remaining three variables (*NDVI, EDGE*) based on the distribution of values represented in the landscape, with the median value being used to define the cutoff between a high value and low value state.

2.3.4 Bayesian Network Model of King Rail Occupancy

The BN model structure (Figure 2.4A) reflected experts' thematic organization of variables between the two occupancy mechanisms of patch access and site selection. The twelve landscape variables (input nodes; Table 2.4) combined to predict the suitability of the habitat for access (*LOCATE*), nesting (*NEST*), foraging (*FORAGE*), and avoiding disturbance (*NODISTURB*). We represented these intermediate nodes as continuous values (range 0 to 1), assigned to the state Suitable (≥0.5 probability of being suitable) or Unsuitable (<0.5 probability of being suitable). The three intermediate nodes *NEST*, *FORAGE*, and *NODISTURB* together predicted the probability that a King Rail would choose to establish a breeding territory at a given location within the patch (*BREED*). We represented the *BREED* node as a continuous value (range 0 to 1), assigned to the state High (≥0.5 probability of establishing a breeding territory) or Low (<0.5 probability of establishing a breeding territory). Finally, two intermediate nodes together (*LOCATE* and *BREED*) predicted the value of the output node, the probability of King Rail occupancy in the breeding season (*KIRA*). The final network had 19 nodes, 18 links, and 182 conditional probabilities. In the absence of any information about a raster cell (i.e., all input node values equally possible; uninformative priors), the BN model predicts the probability of King Rail occupancy to be 0.488 ± 0.26 (Figure 2.4A). This equates to a distribution that places 28.8% of the expectation in the Low category (0 to 0.33 probability of occupancy), 45.0% in the Moderate category (0.33 to 0.66 probability of occupancy), and 26.2% in the High category (0.66 to 1 probability of occupancy).

The Conditional Probability Table for the *LOCATE* node (Figure 2.4B) illustrates how experts hypothesized relationships among input variables and how we entered this information into Netica. *LOCATE* is the probability that a patch is in a suitable location to be accessed by a King Rail

Table 2.4. Summary of available spatial data. Discrete categories were defined for each Bayesian network (BN) predictor variable. We calculated the proportion of 30-m marsh grid cells in the study area and the National Wildlife Refuge (NWR) system falling within each category. We also show the distribution of field survey points within each category.

Predictor Variable Name (BN Input Nodes)	**Description of spatial data used to quantify predictor value**	**Categorical levels defined for BN**	**Percentage of landscape in category** N = 1,002,983 pixels (90,286 ha)	**Percentage of category in NWR System** N = 203,217 pixels (18,290 ha)	**Number of Survey Points** N = 105
Patch[1] level variables					
SIZE	**Patch size**: Number of grid cells in a marsh patch	Small (<8 ha, 900 pixels)	42 (38,249 ha)	8	67
		Medium (8 – 20 ha)	13 (11,449 ha)	20	13
		Large (>20 ha, 2248 pixels)	45 (40,570 ha)	32	25
CONNECT	**Connectivity**: Number of neighboring patches within 250 m of a patch's edge	Low (0 – 2 neighbors)	2 (2,249 ha)	5	2
		High (≥3 neighbors)	98 (88,019 ha)	21	103
TYPE	**Shore vs. Interior Patch**: Presence of at least one marsh grid cell in the patch that shares an edge with a water grid cell	Interior (water edge absent) (1)	5 (4,392 ha)	13	5
		Edge (water edge present) (0)	95 (85,876 ha)	21	100
HIST	**Historical presence**: Presence of King Rail is documented in the Natural Heritage Program database (as represented in SEGAP models)	Undocumented (0)	55 (49,725 ha)	23	31
		Documented (1)	45 (40,543 ha)	16	74
Site[2] level variables					
WATER	**Proximity to water**: Distance to nearest water as mapped by the National Hydrological Data	Near (<100 m)	69 (62,468 ha)	17	86
		Intermediate (100 – 249)	18 (16,566 ha)	22	12
		Far (≥250 m)	12 (11,233 ha)	35	7
SALT	**Salinity**: Categorical classification as fresh/oligohaline, brackish, salt marsh type from SEGAP landcover	Fresh/Oligohaline (<5 ppt)	28 (24,826 ha)	21	105
		Brackish (5 – 15 ppt)	72 (65,236 ha)	20	0
		Salt (>15 ppt)	<0.01 (207 ha)	0.03	0
NDVI	**Vegetative diversity**: Normalized Difference Vegetation Index calculated from 1-m Digital Orthoquarter Quadrangle maps and reported as diversity of values within 30-m pixels to match SEGAP spatial resolution	Low (≤11)	3 (2,303 ha)	69	10
		High (>11)	97 (8,7966 ha)	19	73

[1] Patches are collections of neighboring raster grid cells grouped with the ArcGIS function Region Group using the 8-neighbor rule
[2] Sites are the individual 30-m raster grid cells

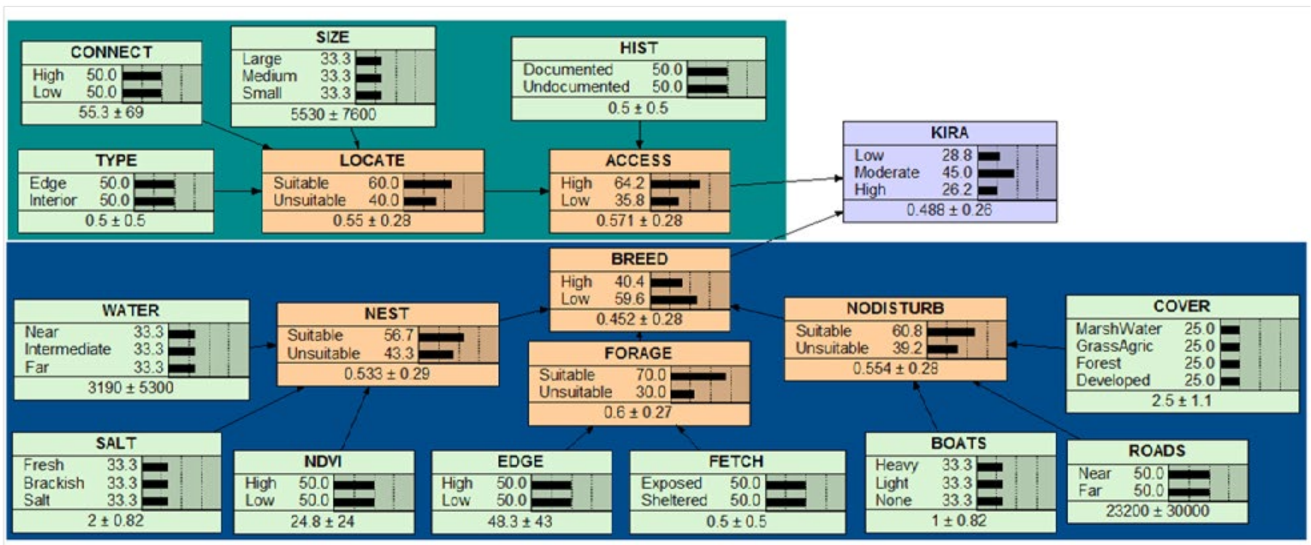
Table 2.4, continued.

Predictor Variable Name (BN Input Nodes)	**Description of spatial data used to quantify predictor value**	**Categorical levels defined for BN**	**Percentage of landscape in category** N = 1,002,983 pixels (90,286 ha)	**Percentage of category in NWR System** N = 203,217 pixels (18,290 ha)	**Number of Survey Points** N = 105
Site level variables (continued)					
EDGE	**Edge habitat available**: Number of marsh grid cells with at least one neighboring water pixel within 250-m radius	Low (≤ 25 edge grid cells*)	49 (4,4436 ha)	22	43
		High (> 25 edge grid cells*)	51 (4,5833 ha)	18	62
		**within 250 m*			
FETCH	**Edge shelter**: Potential exposure of shoreline to high wave action, assigned to all marsh-water edge grid cells bordering large open water areas (e.g., Currituck Sound, Alligator River)	Sheltered (1)	76 (68,868 ha)	22	66
		Exposed (0)	24 (21,400 ha)	13	39
ROADS	**Road disturbance and threat**: Distance to nearest road	Near (≤ 100 m)	7 (6,673 ha)	10	15
		Far (> 100 m)	93 (83,595 ha)	21	90
BOATS	**Boat disturbance and threat**: Expected level of boat traffic	No Data (*)	99 (89,482 ha)	20	105
		Heavy (2)	0	0	0
		Light (1)	0	0	0
		None (0)	1 (787 ha)	40	0
COVER	**Land cover context**: Dominant land cover class within 1-km radius	Unclassified/Ties (*)	>1 (34 ha)	22	1
		Marsh/Water (1)	79 (71,713 ha)	22	41
		Developed/Bare (2)	1 (974 ha)	0	0
		Forest (3)	17 (15,432 ha)	15	54
		Grass/Agriculture (4)	2 (2,116 ha)	1	9

[1] Patches are collections of neighboring raster grid cells grouped with the ArcGIS function Region Group using the 8-neighbor rule
[2] Sites are the individual 30-m raster grid cells
Total number of raster grid cells in the ENCSEVA landscape: 1,1442,89 grid cells

Figure 2.4. Bayesian network. (A) The BN constructed from expert knowledge predicted the probability of occupancy by breeding King Rail. In this example, no site characteristics have been defined (in each input node, all values are equally likely). The model predicts an expected value with standard deviation (KIRA node in upper right: 0.488 ± 0.26 in the absence of site information). This expectation is also illustrated as a probability density function over the three occupancy categories High, Moderate, and Low. The expected value is a function of both accessibility of a patch within a landscape (light blue box) and the quality of breeding habitat at sites within a patch (dark blue box). Where two or more parent nodes join to a child node we created a conditional probability table (CPT) to quantify experts' hypotheses. Two CPTs are illustrated: (B) the node LOCATE and (C) the node KIRA. In the CPTs the conditions (i.e., combinations of input values) are on the left and the probabilities for each possible output state are on the right.

A



B

Node: LOCATE Apply Okay
Chance % Probability Reset Close

SIZE	TYPE	CONNECT	Adequate	Inadequate
Large	Edge	High	100.00	0.000
Large	Edge	Low	100.00	0.000
Large	Interior	High	80.000	20.000
Large	Interior	Low	80.000	20.000
Medium	Edge	High	90.000	10.000
Medium	Edge	Low	85.000	15.000
Medium	Interior	High	70.000	30.000
Medium	Interior	Low	65.000	35.000
Small	Edge	High	25.000	75.000
Small	Edge	Low	15.000	85.000
Small	Interior	High	10.000	90.000
Small	Interior	Low	0.000	100.00

C

Node: KIRA Apply Okay
Chance % Probability Reset Close

ACCESS	BREED	Low	Moderate	High
High	High	2.500	7.500	90.000
High	Low	15.000	80.000	5.000
Low	High	15.000	80.000	5.000
Low	Low	95.000	4.000	1.000

seeking breeding habitat. *LOCATE* is a function of patch size (*SIZE*: Large, Medium, or Small), the presence of marsh/water edge (*TYPE*: Edge or Interior), and connectivity (*CONNECT*: High or Low). At large patch sizes, experts expected *CONNECT* to have no effect (e.g., Large, Edge, High = Large, Edge, Low = 100% probability of suitable patch location). At small patch sizes, however, experts expected high connectivity patches have a 10% higher probability of being accessed by King Rail (e.g., Small, Edge, High > Small, Edge, Low). In the absence of any information about *SIZE*, *TYPE*, and *CONNECT*, the BN model predicts the probability of suitable access to be 0.55 ± 0.28 (Figure 2.4A). All conditional probability tables are presented in Appendix 2.3.

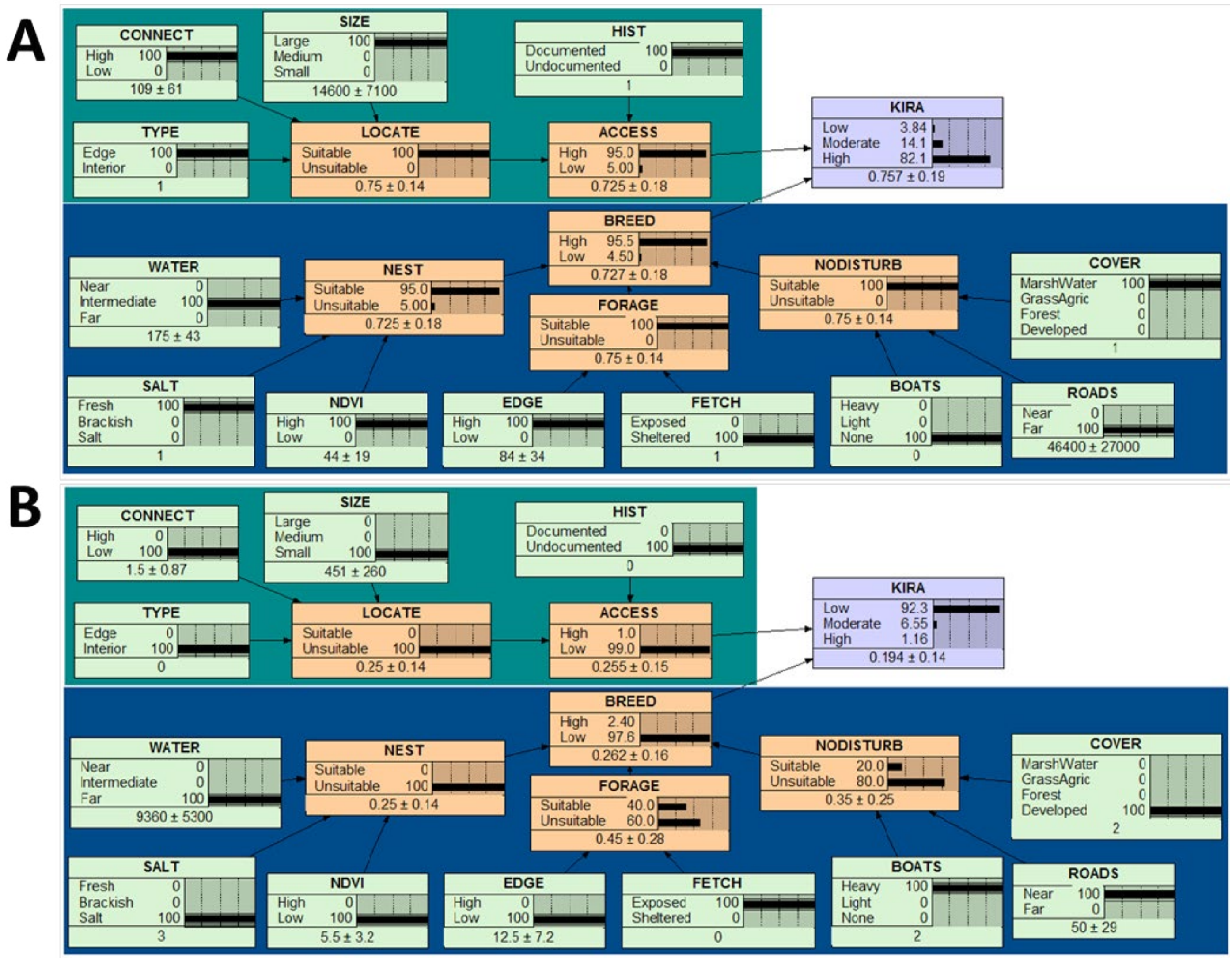
Relationships between input covariates and output responses were also defined in Conditional Probability Tables. The Conditional Probability Table for the *KIRA* node (Figure 2.4C) illustrates how experts defined the probability of King Rail occupancy as a function of patch access (*ACCESS*: Low or High) and breeding site selection (*BREED*: Low or High). Experts were very aware of the complexity and variability of ecological systems; they did not define any combination of states as having 100% or 0% probability of occupancy. They believed it was possible that a King Rail could occupy poor habitat (e.g., Low, Low has a 0.01 probability of High occupancy) and possible that a King Rail could fail to occupy good habitat (e.g., High has a 0.025 probability of Low occupancy). Experts' knowledge was insufficient to infer whether Low *ACCESS* or Low *BREED* would be worse for King Rail occupancy, so these were scored equally.

Expert awareness of complexity and uncertainty is also demonstrated by viewing results for the best possible (Figure 2.5A) and worst possible (Figure 2.5B) combination of landscape values. Under the best possible conditions (i.e., corresponding "best" categorical value selected for each variable, as indicated by the 100% entry), the BN model predicts an expected value for the probability of occupancy of 0.757 ± 0.19. This equates to a distribution that places 82.1% of the expectation in the High probability category, but allows for uncertainty because there is 14.1% in the Moderate probability category, and 3.84% in the Low probability category. Under the worst possible conditions, the BN model predicts an expected value for the probability of occupancy of 0.194 ± 0.14. This equates to a distribution that places 92.3% of the expectation in the Low probability category, but allows for uncertainty because there is 6.55% in the Moderate probability category, and 1.16% in the High probability category.

2.3.5 Verification of the Model Structure

Experts were not wholly consistent when ranking variables individually during discussions versus when evaluating variables jointly within the Conditional Probability Tables. In the interviews, experts had ranked, in order, *NDVI, SIZE, CONNECT, WATER, EDGE* and *TYPE* as the mappable variables likely to have the strongest influence. Variance reduction analysis of the BN models (Table 2.5), however, dropped *NDVI, CONNECT*, and *WATER* to much lower scores, and raised the relative rank score of *SALT, HIST* and *FETCH*. In the expert-only BN model, marsh salinity (VR(*SALT*) = 0.0058) and marsh patch size (VR(*SIZE*) = 0.042) had the greatest potential to influence the probability of King Rail occupancy, followed by historical presence/absence (VR(*HIST*) = 0.0014) and the amount of available edge habitat (VR(*EDGE*) = 0.0010). The response variable (probability of occupancy) was least sensitive to the remaining variables, reflecting experts' description of King Rail as fairly generalist in their marsh habitat preferences, so long as the patch provided enough fresh/brackish marsh for a breeding territory. The differences between experts' ranking of variables

Figure 2.5. Example predictions of the Bayesian network. Input nodes each now have one value indicted as 100% likely (i.e., the value measured from the spatial data). The expected value for the probability of occupancy is shown in the blue boxes. (A) The best possible combination of landscape characteristics predicted an expected value of 0.76 ± SD 0.19. (A) The worst possible combination of landscape characteristics predicted an expected value of 0.19 ± SD 0.14.



outside the BN versus the ranking observed within the BN is not surprising, given that the latter considered all probabilities within the whole model simultaneously – too complex a task for experts. Although they hypothesized habitat preferences based on their knowledge of King Rail and marsh bird species generally, experts did not hypothesize strong or limiting responses for any variable. Acknowledging their own high uncertainty regarding variable ranks and probability estimates, experts reviewed, and by consensus accepted, the Conditional Probability Tables with minor edits. They stated that the tables offered plausible representations of their hypotheses regarding King Rail habitat relationships and distribution patterns.

Table 2.5. Variance reduction analysis results. Given the structure and conditional probability table values in the original BN, the input nodes SALT, SIZE, and HIST had the greatest potential to influence occupancy predictions. Patch access (ACCESS) and site selection (BREED) were roughly equal in their potential to influence the response. Of the mechanisms driving site selection, the suitability of habitat for nest construction had greater potential to influence the response than either suitability of habitat for forage or avoidance of anthropogenic disturbance.

Landscape Variables (BN Input Nodes)	**Suitability Criteria** (BN Intermediate Nodes)	**Occupancy Mechanisms**
SIZE 0.0042	**LOCATE** 0.0088	**ACCESS** 0.0203
CONNECT $2.295e^{-5}$		
TYPE 0.0003		
HIST 0.0014		
WATER $1.988e^{-5}$	**NEST** 0.0088	**BREED** 0.0229
SALT 0.0058		
NDVI $3.976e^{5}$		
EDGE 0.0010	**FORAGE** 0.0052	
FETCH 0.0002		
ROADS $5.696e^{-6}$	**NODISTURB** 0.0002	
BOATS $5.491e^{-7}$		
COVER $4.546e^{-5}$		

<u>2.3.6 Spatially-Explicit Occupancy Predictions</u>

Application of the BN to the landscape reveals the Ecoregion to be diverse in both the predicted probability of King Rail occupancy and in the confidence of the predictions (Figures 2.6 and 2.7). The raster grid cells that had been identified as Potential Habitat by SEGAP, now are attributed with a continuous probability of occupancy value (occupancy by King Rail during the breeding season based on landscape characteristics). Potential Habitat is now seen to be composed of 40% High, 16% Moderate, and 44% Low probability of occupancy habitat (Figure 2.8). Most land in each occupancy category remains unprotected (Table 2.6); however, the High category has the highest percentage of land in conservation (47%; Table 2.6). Incorporating probabilistic predictions of habitat occupancy (versus simply predicting potential habitat/non-habitat) changes how refuges rank in terms of their likely contribution to King Rail conservation. While Mackay Island ranked fourth in area of King Rail Potential Habitat, this refuge ranked second in area with High probability of occupancy habitat (Table 2.7). Pocosin Lakes has a small area of marsh identified as Potential Habitat, but these are predicted to have only Moderate or Low probability of occupancy by the BN (Table 2.7).

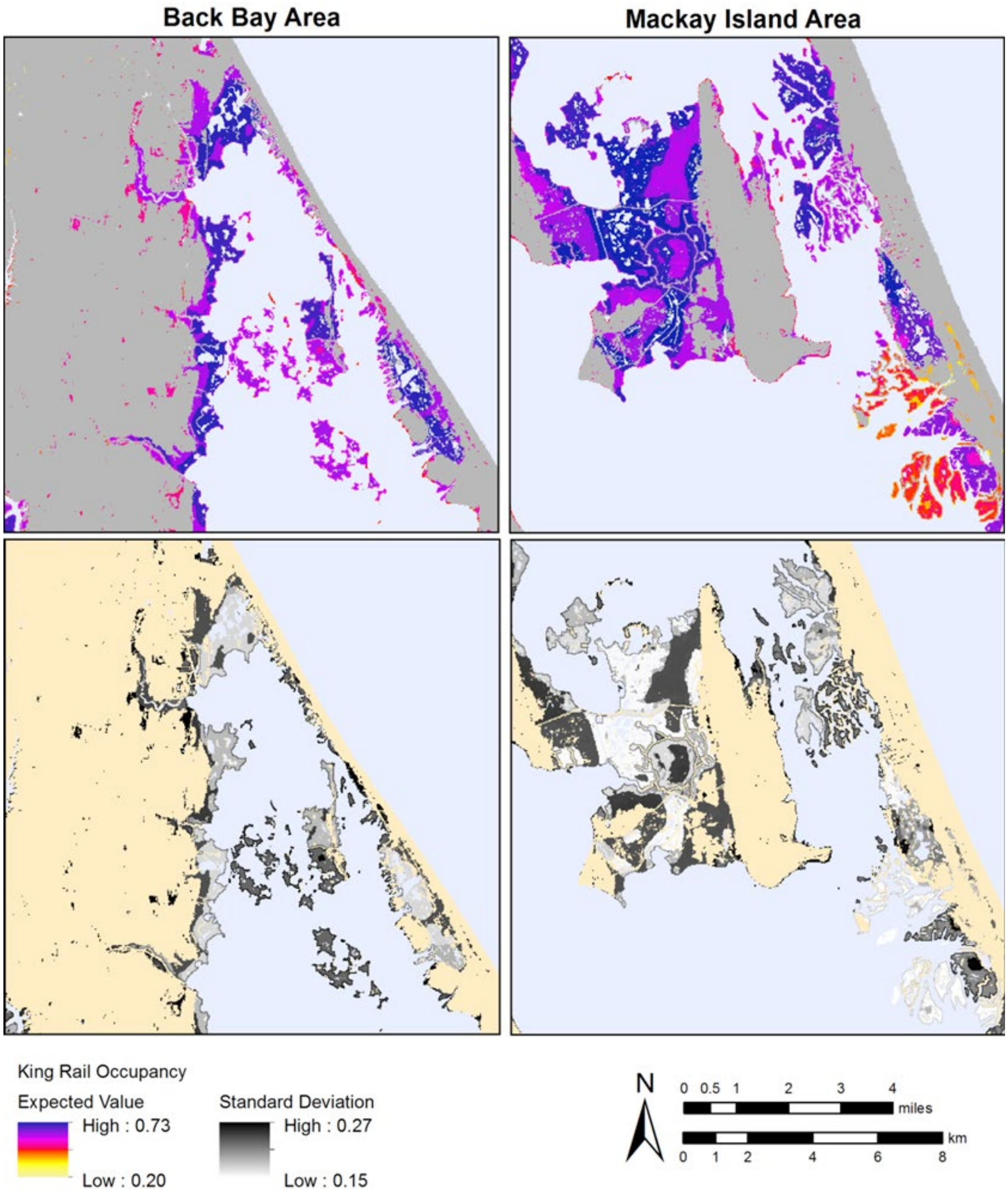


Figure 2.6. Example results: Back Bay and Mackay Island regions. Results of application of Bayesian network equation to Ecoregional landscape. The expected probability of occupancy is shown in the top row and the standard deviation of the expectation is shown in the bottom row.

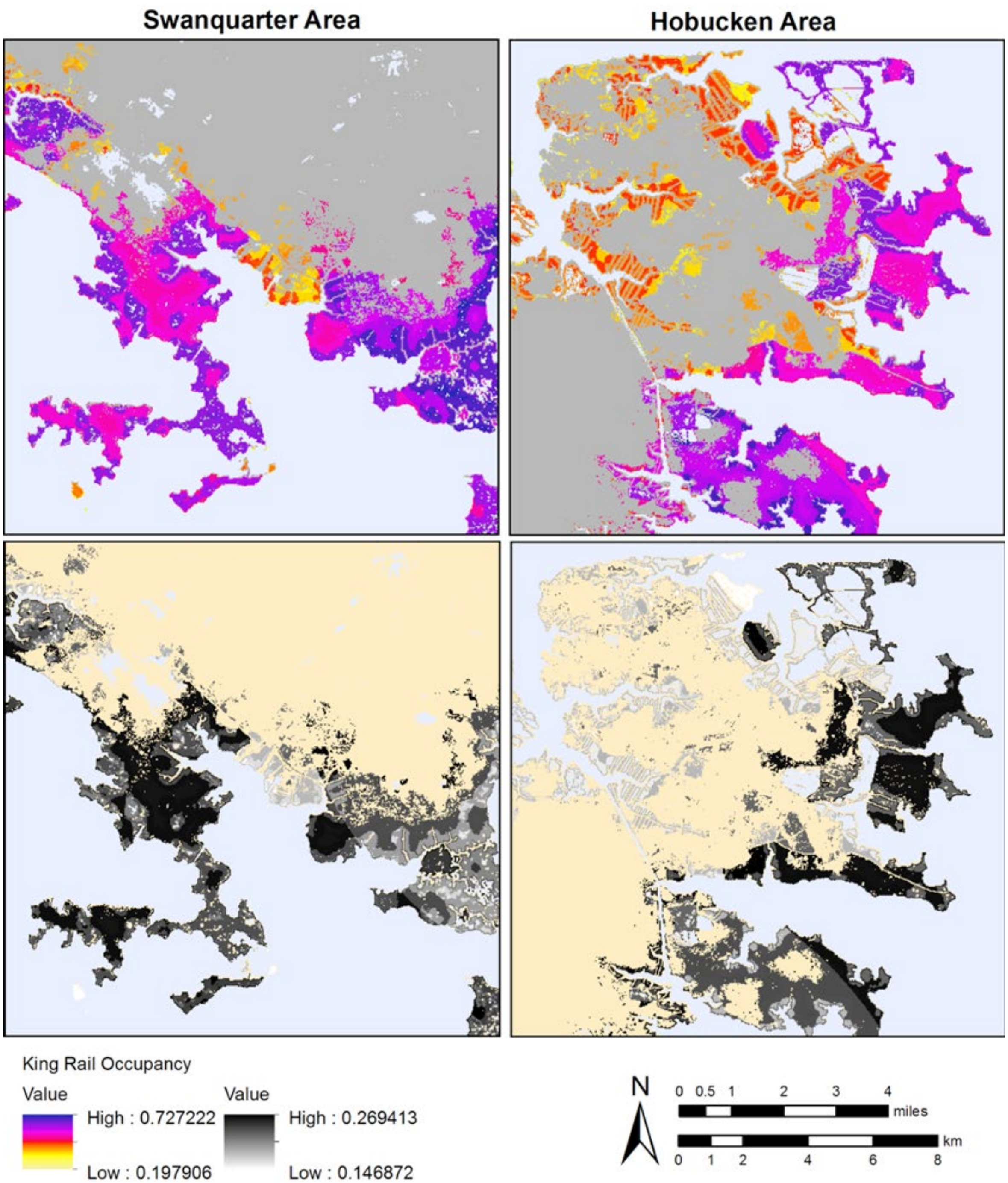


Figure 2.7. Example results: Swanquarter and Hobucken regions. Results of application of Bayesian network equation to Ecoregional landscape. The expected probability of occupancy is shown in the top row and the standard deviation of the expectation is shown in the bottom row.

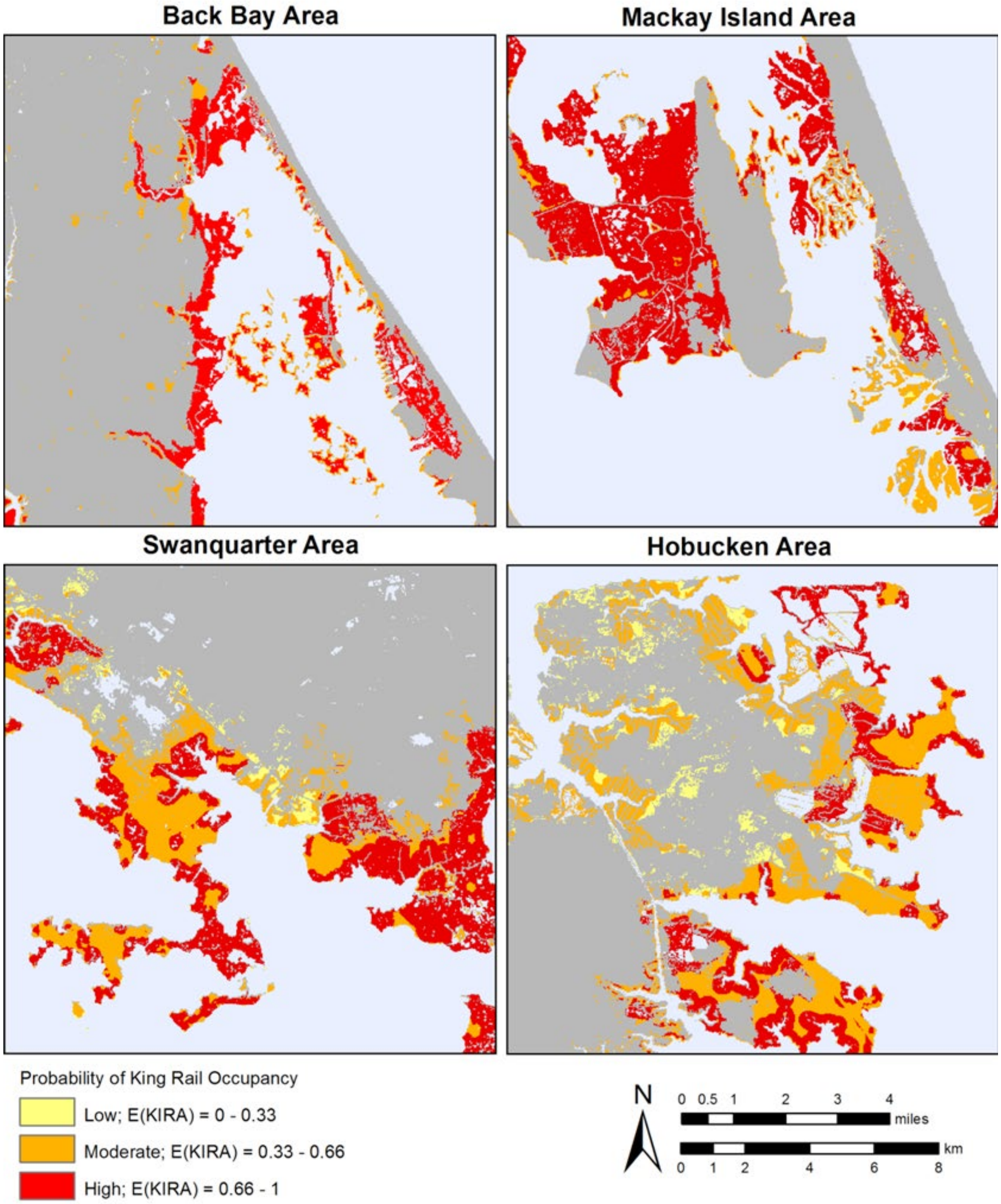


Figure 2.8. Categorical probability of occupancy. Results of application of Bayesian network equation to Ecoregional landscape. The probability scale has been discretized into three equal interval categories. The most likely categorical value (e.g., Low, Moderate, or High) corresponding to the expected probability of occupancy is mapped for all four example areas.

Table 2.6. Occupancy categories summarized by GAP Conservation Status. Area and percentage of landscape classified as Low, Moderate, and High probability of occupancy calculated for each GAP Conservation Status category. GAP Status 1 and 2 lands have the highest degree of protection and management for conservation. Status 3 lands may have some protection or management, but also support multiple uses, including resource extraction (forestry, mining, etc.). Status 4 lands are either unprotected or of unknown management intent.

	Predicted Occupancy Category ha (% of category total)		
GAP Conservation Status	High	Moderate	Low
1	5751 (14%)	5629 (12%)	303 (2%)
2	9329 (22%)	7175 (16%)	1420 (9%)
3	4443 (11%)	5075 (11%)	1707 (11%)
4	22142 (53%)	27302 (60%)	12620 (79%)
Total	41665	16050	45180

Table 2.7. Occupancy categories summarized by National Wildlife Refuge. Area and percentage of landscape classified as Low, Moderate, and High probability of occupancy calculated for each National Wildlife Refuge and non-refuge lands within the Ecoregion

		Predicted Occupancy Category ha (% of refuge Potential Habitat)		
National Wildlife Refuge	**Total Potential Habitat** (ha)	High	Moderate	Low
Alligator River	4889	1336 (27%)	3045 (62%)	509 (10%)
Back Bay	1384	1039 (75%)	340 (25%)	5 (<1%)
Cedar Island	954	404 (42%)	522 (55%)	28 (3%)
Currituck	3779	1138 (30%)	2578 (68%)	63 (2%)
Great Dismal Swamp	0	0	0	0
Mackay Island	2077	1993 (96%)	84 (4%)	0 (0%)
Mattamuskeet	0	0	0	0
Pea Island	846	525 (62%)	272 (32%)	49 (6%)
Pocosin Lakes	160	0	83 (52%)	77 (48%)
Roanoke River	3	0	<1 (3%)	3 (97%)
Swanquarter	4200	2658 (63%)	1498 (36%)	44 (1%)
Non-Refuge lands	84693	32594 (38%)	36791 (43%)	15307 (18%)

2.3.7 Model Validation

2.3.7.1 King Rail Detection

King Rails were detected at least once at 34 of the 105 surveyed marsh points, giving a naïve occupancy estimate (unadjusted for detection probability) of 0.324 (see Chapter 3 for details of sampling design, methods, and results). We observed annual differences in detection, but the data were inadequate to partition the sources of this variation. Though not so extreme as flood or drought conditions, we anecdotally noted the 2008 season was exceptionally wet, while the 2009 season was exceptionally dry. Also, based on call frequency, our first field season seemed to commence and end slightly later than the period of King Rail breeding. Field crews reported no King Rail calls during the third sampling period of the first season (i.e., each season had three, 3-week sampling periods), whereas in the second year, King Rails called throughout all sampling periods. Therefore, detection probability was constant neither between years nor between sampling periods. The temporal trend in detection was best represented as dependent on year and sampling period for year 2008, but constant for 2009.

2.3.7.2 King Rail Detection-Adjusted Occupancy

We used detection-adjusted occupancy values from an independent model (see Chapter 3 for model details) as the observed occupancy values in the model validation analyses. This independent model, generated in the program PRESENCE, used not only landscape data, but also microhabitat data collected during field surveys (see Chapter 3). The model with potential habitat status (True/False), shrubby vegetation (present/absent), and landscape variables *SIZE* and *CONNECT* received the greatest weight (AIC*w* = 0.82) when compared against model sets with other combinations of microhabitat and landscape variables. No other model was competitive with this top model (all ΔAIC ≥ 3.6), thus we selected this model to serve in comparison to the BN model predictions.

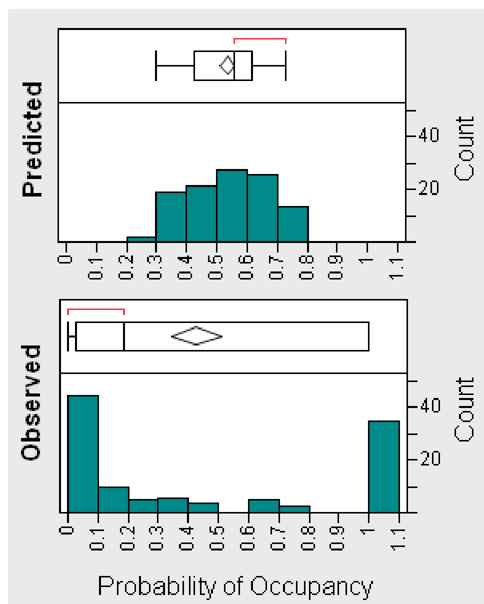


Figure 2.9. Predicted and observed probability of occupancy. Histograms illustrate the different distributions of predicted and observed occupancy. The BN predicts the asymptotic occupancy (long-term probability of site occupancy), while the observed occupancy calculated in PRESENCE is the instantaneous occupancy (the probability that a pair is present or absent at the site that year).

2.3.7.3 Validation Analyses

The expected values predicted from the BN model approximated a normal distribution (Figure 2.9: $\bar{X}$ = 0.536, median = 0.558, SD = 0.126), but the observed occupancy values from the top PRESENCE model were negatively skewed and over-dispersed (Figure 2.9: $\bar{X}$)= 0.427, median = 0.184, SD = 0.432). A pair-wise t-test of the predicted versus the observed occupancy values rejected the null hypothesis of equality only if the threshold for rejection was set to P = 0.001 (Table 2.8: t-test, P = 0.006). Netica's test-with-cases function returned an overall error rate of 60 percent when the response was discretized into the three equal-interval categories: Low, Moderate, and High probability of occupancy. Analysis of the error matrix found the degree of matching between the observed and predicted categorical values barely exceeded what would be expected by chance (Table 2.9: Kappa statistic = 0.05). The model was overly optimistic; the probability of occupancy was over-estimated far more frequently than it was under-estimated (Table 2.9: ratio = 57:26). This result is not surprising, given that the BN model predicts the potential for occupancy given a subset of criteria that determine species distribution patterns (i.e., the model excludes biological interactions such as predation and competition).

Table 2.8. Pair-wise comparison of predicted versus observed occupancy values. A two-tailed t-test assuming unequal variance (red text) was significant (α = 0.05) with P = 0.01.

Paired Two Sample t-test

Probability of Occupancy by Breeding King Rail	*Predicted*	*Observed*
Mean	0.536	0.427
Variance	0.016	0.186
Observations	105	105
Pearson Correlation	0.374	
Hypothesized Mean Difference	0	
df	104	
t Stat	2.780	
P(T<=t) one-tail	0.003	
t Critical one-tail	1.660	
P(T<=t) two-tail	0.006	
t Critical two-tail	1.983	

Table 2.9. Error matrix. The error matrix of predicted versus observed occupancy categories. The distribution is non-random (Kappa statistic = 0.05) with over-predictions twice as common as under-predictions.

Probability of Occupancy by Breeding King Rail

	Observed		
Predicted	High	Moderate	Low
High	12	3	5
Moderate	25	5	49
Low	0	1	5

Kappa Statistic = 0.05

2.4 Discussion

The construction and validation of the BN advanced the science of King Rail management in three critical ways, demonstrating the value of this approach as a foundation for adaptive management. First, by organizing the gathered information within a BN, the previously latent expert knowledge was formally stated as process-based hypotheses. Second, by linking these hypotheses to spatial data and mapping the resulting expected probability of occupancy, it became possible to test occupancy hypotheses. Third, by incorporating uncertainty, the models communicate the risk involved in selecting locations for action and managers thereby gain a critical piece of information necessary for decision analysis.

2.4.1 Formal Organization and Summary of Available Knowledge

Data-poor species are also often expert-poor species, as illustrated by our King Rail case study. Although our five experts were all familiar with King Rail, all were hesitant to identify variables and provide probability estimates in the absence of a structured, empirical study of King Rail breeding ecology and habitat associations. We found it helpful to emphasize the role of the network as a means to formulate, structure, and visually communicate assumptions and hypotheses. We emphasized how their knowledge would serve as the foundation of an adaptive management and monitoring program, rather than functioning as a final product that would constrain all future decisions. We also reassured experts that their uncertainty would be directly incorporated into the model and reported along with the model's predictions. In this manner, their elicited knowledge and "best professional judgment" were less likely to be misrepresented as "empirically observed and experimentally tested fact". We noted that most elicited knowledge was inferential, as experts drew upon general ecological theory and marsh bird ecology, as much as from their personal observations of King Rail.

Although the literature review yielded few insights to landscape-scale King Rail habitat associations and no local information, it still performed several valuable functions. Reading and categorizing the literature oriented the project staff to the state of knowledge which they would soon elicit and model. In particular, it provided the researchers preparing to conduct the elicitations and construct the expert-based models familiarity with common methods and proficiency with the specialized terminology, both valuable to improve the language of the elicitation questions. Published studies provided insight into the scale of observation common to investigations of marsh bird ecology. It was quickly clear that experts would struggle to define landscape scale species-habitat relationships as such patterns and processes were outside their usual experience. This knowledge guided us to incorporate more introductory material and visual examples into the elicitation orientation materials. By these means, the literature review served as a bridge to facilitate communication across scales and between disciplines.

It took an iterative, trial-and-error approach to define an appropriate structure for the BN which simultaneously captured, yet worked within the constraints of, expert knowledge and available spatial data. In the original elicitations, we had asked experts to comment directly on landscape-occupancy relationships and the experts struggled with this task. However, in review of our elicitation notes, we observed that experts' comments repeatedly referenced mechanisms of habitat access and habitat selection when considering landscape attributes. When we organized our network around these two distinct ecological processes, experts much more easily proposed and ranked landscape variables.

Once experts proposed a set of landscape variables likely to influence King Rail occupancy, transcribing these into spatially-explicit hypotheses through the use of geographic information systems (GIS) posed a major challenge. Our experts were unfamiliar with the available spatial data and method of processing spatial data, thus there was a high risk of misrepresenting their hypotheses when selecting proxy data. For example, although experts readily identified patch size as an important variable, the definition of patch size within a GIS involves many data processing decisions. With raster data, a GIS requires specification of a four-neighbor (neighboring cells share edges only) or eight-neighbor (neighboring cells share edges or corners) rule to identify and calculate the size of unique patches. Similarly, the grain (i.e., cell size) of the raster data may result in patch divisions that are not ecologically meaningful. In our patch calculations, for simplicity, we allowed a single row of water cells to serve as a division separating two marsh patches, even though the 30-m distance this represented by this single row likely did not serve as a dispersal barrier to King Rail. Experts frequently chose to adjust their initial responses once they understood the differences between the scale of their observations relative to the scale of the data. For example, experts decreased the emphasis on edge and interspersion of marsh-water habitats, once they realized that only large open water bodies (≥30-m grid cell) would be included in such a metric when calculated on land cover raster data.

2.4.2 Spatially-Explicit, Testable Occupancy Predictions

Previous King Rail population and habitat estimates and objectives had been made based on estimates of total marsh habitat area or the area of marsh classified as potential habitat. Even with their limited expertise, the participating experts clearly recognized that all potential pabitat in the Ecoregion was not equally likely to be occupied by breeding King Rail. Despite the many challenges, they were cautiously satisfied that the final BN model captured their knowledge of King Rail and represented rational hypotheses (and uncertainty) regarding landscape-occupancy relationships. The resulting maps offered the first opportunity for the experts, as well as other local biologists and land managers, to view a spatially-explicit representation of their hypotheses and associated uncertainty.

It is important to note that our models did not simply predict "occupancy", but rather "occupancy given a set of methods and assumptions". We designed our expert elicitations and resulting BN models to predict occupancy given a specific population survey method (Standardized Marsh Bird Call-Back) and statistical framework (PRESENCE). While some experts did not fully support these survey or statistical methods, this level of specification was necessary to validate (and update) of the model. If a method had not been clearly stated initially, then differences among experts or later, differences between predicted and observed values, could reflect different assumed methods rather than true error or uncertainty. Also, by specifying a method *a priori,* learning focuses on the linkages between the spatial data and occupancy, rather than the best method to measure occupancy.

Despite the effort to closely match the methods and units of the BN model predictions and empirical measurements of occupancy, the predictions and measurements do differ in a few important ways. The empirical methods to calculate detection-adjusted occupancy require an assumption of closure and calculate a value that is specific to a given season (MacKenzie et al. 2006; MacKenzie et al. 2002). In BN models, however, the predicted probability of occupancy depicts an expectation more similar to a long-term average. Efford and Dawson (2012) make a distinction between instantaneous occupancy (MacKenzie et al. 2002) and asymptotic occupancy (Tyre et al. 2003) which is useful in this context. Asymptotic occupancy reflects the cumulative observation of occupancy over time (Efford and Dawson 2012), a concept much closer to the knowledge accumulated by experts and also more appropriate to support the needs of management decisions. In brief, PRESENCE measures instantaneous occupancy to answer "What is the probability that this site is occupied by breeding King Rail this year (or other period of study)?", while the BN predicts to answer "What is the probability that this site is occupied in any randomly selected year ?" The inflated error when the BN predictions (majority of predictions had a moderate probability of occupancy at any given time) were compared to the PRESENCE estimates (most sites had high or low probability of occupancy in a single season) may partly be a result of these model differences. More work should be done to explore the ramifications of these differences and to confirm that the continued training of the BN with annual data will eventually produce the expected asymptotic occupancy predictions.

The extreme variation in environmental conditions in our sampling period illustrated a common challenge when using short-term empirical studies to validate models that represent probabilities reflecting long-term averages. The extreme wet and dry conditions of our field seasons were atypical and, though not likely extreme enough to significantly increase mortality or regional emigration, possibly were not optimal conditions for King Rail. Neither year could be expected to provide validation data well matched to the long-term average conditions elicited from experts and represented in the BN models. We did not collect weather data, but we hypothesize that the atypical conditions could partially explain the high error rate for a model constructed from expert knowledge elicited in reference to typical conditions.

2.4.3 Capturing Uncertainty to Support Better Management Decisions

The BN models not only predict occupancy on a continuous scale, but also report the uncertainty of each prediction as a standard deviation. The maps included in this report illustrate how the greater precision of these estimates allow differentiation of various Potential Habitat areas and comparison of occupancy expectation among refuges (or other land units). With these continuous data, managers could define project specific thresholds for occupancy and uncertainty. In some cases, depending on a manager's risk aversion, acquiring a parcel of land with a high certainty of having a moderate probability of occupancy might be preferred to acquiring a parcel with a low certainty of high probability of occupancy. Similarly, the new maps support a more nuanced assessment of existing population and habitat distribution. Although a probability of occupancy of 0.5 is a common default threshold for distinguishing occupied from unoccupied habitat, there could be cases when a more (or less) conservative threshold would be appropriate (see Chapter 4).

2.5 Conclusions

Construction of expert-based models is not a short-cut to successful conservation or a replacement for field studies. Reliable expert-elicitation requires careful planning and preparation, and rigorous procedures, to ensure that the appropriate questions are posed and the responses appropriately interpreted. Multiple iterations of model structural design and review are necessary to accurately capture and represent expert knowledge within BNs. To provide a firm foundation for adaptive management and systematic learning, the elicitation and knowledge encoding methods used must be rigorous, transparent, and repeatable. During the period of model development, the science of expert-based modeling in landscape ecology has advanced rapidly (see reviews in Krueger et al. 2012; Perera et al. 2011) leading to published recommendations and the creation of new tools (e.g., Low Choy et al. 2011) which together facilitate more rapid, yet more rigorous expert elicitation.

Given the intensive effort to gather and encode expert knowledge, the performance of the expert-based BN model, as tested by our validation data, at first may appear disappointing. However, our goal was not to build a final model, but to construct a solid foundation for adaptive management that would help managers identify key areas for monitoring and research, and that would improve information over time by incorporating the results of such efforts into model updates. The poor classification performance of our model indicates, at least in part, that some aspects of the experts' knowledge may be inaccurate or may be inaccurately represented by the proxy spatial data. In addition, we identified a potential mismatch between the definition of occupancy in the expert-based model as compared to how occupancy is calculated from specific, short-term field studies. This lesson is valuable in guiding how future modeling efforts can be made more consistent with field studies, and *vice versa*. Our results also point to the need for caution when applying expert-based models that have not yet been validated, even when these models have been verified by independent experts. The following chapter illustrates how the expert-based BN models serve to guide adaptive monitoring and improve model performance.

Chapter 3

POPULATION AND HABITAT MONITORING TO VALIDATE AND UPDATE BAYESIAN NETWORKS

Table of Contents

3.1 Introduction

Our project incorporated a field research component to explore and demonstrate how Bayesian network (BN) models could support learning within an adaptive management framework. To this end, we addressed several objectives. First, the sampling design demonstrated how knowledge of model uncertainty could guide productive allocation of limited monitoring resources. Second, the integration of field monitoring data into the original model demonstrated the process and outcome of model updating. Third, locally collected field data suitable for occupancy modeling in PRESENCE allowed direct validation of the BN model predictions. Fourth, and finally, side-by-side comparison of the BN and PRESENCE models provided insight into the advantages and disadvantages of expert-based modeling relative to data-driven modeling processes.

Surprisingly, although BNs are promoted as adaptive management tools in wildlife conservation and management, published guidelines do not outline design criteria for an effective monitoring strategy in support of adaptive learning. Several papers detail methods to validate and update expert-based BNs with empirical data (e.g., Marcot et al. 2006), but the data used in these examples is obtained without further explanation of sampling design decisions. Marcot et al. (2006) provide this simple recommendation: "Validation data would be collected through statistically-based field sampling, where species presence and values of the predictor variables… are recorded from randomized plots or from plots on which the results of the model were being applied by the manager." Marcot et al. (2006) warn against assigning data too much weight if the number of cases for updating is few, but do not clarify how to determine how much data are adequate or what weighting scheme would be appropriate. Rowland et al. (2003) note that their empirical data (i.e., wolverine, *Gulo gulo*, data from the Natural Heritage Program) were neither systematically nor randomly collected and likely included biases related to the uneven sampling effort across the study region, but do not comment on how these characteristics might impact model validation or updating.

Expert-based BN models represent untested hypotheses that must be validated and updated with empirical data before applying to management questions. To evaluate the potential value of expert-based BN models to achieve Strategic Habitat Conservation, USFWS must know the initial and ongoing sampling effort required to achieve a useful level of predictive accuracy. Too often model validation is simply a step to check that empirical observations match (or fail to match) model predictions. Then, if the model performs poorly, it is discarded. BN models are constructed to facilitate learning, yet this learning requires that sampling strategies are built upon clear learning objectives. Prioritizing among learning objectives will be necessary for the USFWS and partnering organizations which have limited resources to establish intensive monitoring programs.

To address the questions of sampling strategy and effort, we considered the major sources of potential error in an expert-based BN. These sources relate to errors in expert knowledge, errors in model specification, and errors in the spatial data upon which the BN equations are projected.

Errors in expert knowledge have received the most attention in the literature. Various sources of cognitive bias can distort experts' reporting of their own experiences and guidelines exist to recognize and reduce such errors (Kynn 2008; Cooke 1991). If experts are unfamiliar with probability theory, the use of pre-elicitation training, graphical visual aids, and even indirect elicitation (e.g., eliciting frequency rather than probability of events) are recommended strategies to improve experts' accuracy in reporting their own experiences (Low-Choy et al. 2011; Kuhnert et al. 2010;

Denham and Mengersen 2007). Potential errors introduced during model specification include incorporating spurious variables, excluding key variables, poorly discretizing variables, and incorrectly defining conditional probabilities. Model verification will check that these aspects conform to experts' understanding of the system, but if experts' understanding is incorrect, then these errors can only be identified and corrected with empirical data. The accuracy and precision of any spatially-explicit prediction is limited by the accuracy and precision of the underlying spatial data. Spatial data are often models in their own right, either interpreted from remotely-sensed imagery or interpolated from empirical data measured at specific points. If the accuracy of these data is unknown, the accuracy of the species-habitat models built upon them cannot be known. Furthermore, if the expert-based model fails, it would be impossible to know whether the failure reflected error in the model, error in the data, or both. Therefore, it was our objective to design a strategy that would allow us to distinguish among various possible sources of model error and thereby ensure advancement of King Rail management and conservation, even if the initial BN models performed poorly.

Demonstrating strengths and weaknesses of BN learning was the major objective of our validation process. Data available to us and the modeling options within Netica presented a myriad of choices regarding how learning could proceed, yet we could find no clear guidance to select a preferred strategy. We therefore conducted a series of validation tests which explored such questions as: Does it matter if samples are drawn predominantly from habitat where occupancy is expected? Is it better to keep or discard the expert-knowledge, once empirical data have been collected? By posing such questions, we use the King Rail case study as the foundation of general recommendations to improve learning applications of BNs within adaptive management settings.

3.2 Methods

3.2.1 Sampling Design

3.2.1.1 Hierarchical Stratified Random Design

Our surveys in 2008 and 2009 were specifically designed to validate and update the BN model based on a specific set of assumptions and objectives. First, we assumed that within a Strategic Habitat Conservation framework both management and monitoring would evolve adaptively. Second, we assumed that refuge resources for monitoring would be limited. Based on both these assumptions, we took a minimalist approach to study design by stratifying on only three of the variables. Under an adaptive monitoring strategy, sampling design should target sources of greatest uncertainty and then, as the uncertainty is reduced, sampling effort is reallocated to other sources of uncertainty. Importantly, data are collected for all variables, but the balanced representation of the targeted variables allows for stronger inference than the possibly unbalanced representation of the non-target variables. Third, given Strategic Habitat Conservation's emphasis on landscape scale perspectives and collaboration, we assumed the model was intended to manage Ecoregional King Rail populations and habitat. As BNs are updated, they become more specific to the region (or time) from which the data are collected. By spreading sample sites across the Ecoregion (as much as feasible with available resources), we designed a sampling strategy that would, in theory, cause the BN to become tuned to patterns and variation within the Ecoregion rather than a subunit within the Ecoregion. We also disregarded ownership and management status when we selected the sample sites. Refuges are relatively large and relatively intensively managed compared to much of the privately held marsh outside refuge boundaries. By sampling on and off refuges, we hoped to remove this possible sampling bias and provide a more accurate picture of the Ecoregional population status, while also possibly demonstrating the role of BN as a guide for Ecoregional collaboration. Fourth, we assumed that errors predicting Low probability occupancy sites were of equal concern as errors predicting High probability occupancy sites. Some conservation decisions are more sensitive to Type I error (i.e., predicting occupancy where a species is not present, also called false positives or commission errors), while others are more sensitive to Type II error (i.e., predicting absence at an occupied site, also called false negatives or omission errors). Because our model did not specify a specific decision, we sampled across a full range of High to Low probability sites to ensure learning occurred across this spectrum.

To achieve the objectives outlined above, we selected sites based on a hierarchical stratified design. First, we placed a randomly initiated 400-m grid over the entire Ecoregion landscape. Four hundred meters is the minimum distance suggested for two call-back surveys to be considered independent samples (Conway 2009; 2008a). Points falling in marsh habitat were attributed with the underlying potential habitat landscape data values. Points falling outside marsh habitat were attributed with the underlying coarse land cover class (grass/agriculture, developed/bare, or forest). We then stratified the marsh points according to three variables: patch size (Large, Medium, or Small), dominant land cover class within 1-km radius (Marsh & Water, Agriculture, Forest, or Urban & Other), and distance to nearest open water (Near, Intermediate, or Far). We selected these variables because (1) data were available across the full project extent; and (2) they offered important potential for learning within the BN. Patch size was the highest ranked expert-identified landscape variable with complete spatial coverage. In the BN sensitivity analysis, it had also received a high variance reduction score. Distance to water and land cover context both corresponded to high expert uncertainty, with strong logical arguments but no supporting data. King Rail observations had only ever been conducted at the marsh edge, and observers had never considered the landscape context of their observations. One hundred marsh points were then randomly selected from each strata as possible sample points. Twenty non-marsh points were randomly selected from each of three non-marsh land cover classes to provide a minimal level of ground-truthing for the land cover classification data that form the foundation of the BN models and the sampling strategy. Non-marsh survey points were only visited once and were not included the BN or PRESENCE models.

Although all twenty-four possible strata combinations were represented in the Ecoregional landscape, not all were equally represented or equally accessible to the field crew. The second stage of the sampling design therefore addressed issues of sampling efficiency given variable weather conditions and site access. Maps noted the locations of the randomly selected points. The crew used these maps to plan their daily survey routes to meet two criteria: (1) obtain a minimum of six samples per strata (which required they collect data from three points per day on average) and (2) maximize the geographic distribution of samples from each strata throughout the Ecoregion. In 2008, two field crew teams used these methods to select sites and conduct call-back surveys north and south of the Albemarle Sound. In 2009, one team worked the area north of Albemarle Sound.

3.2.1.2 Non-Random Design

An independent King Rail research project was conducted in the Ecoregion in 2010 (Rogers et al.

2013; Rogers 2011). This study used our equipment and followed the same procedures to conduct call-back surveys. Sites in this study were also selected from our initial randomized 400-m grid. However, the selection of sites from the grid was not based on a stratified design. Instead, because the goal of this study was to locate nests to monitor reproduction success, only sites expected to have a High probability of occupancy based on the BN model were identified as potential survey sites. These sites did, however, differ in the time since most recent prescribed burn.

Occupancy data from the 2010 study provided a unique opportunity to examine the effect of using unbalanced data to validate and update a BN. As most published wildlife conservation BN models similarly borrow data from independent studies to test their models, any difference in the learning potential would be important information for the USFWS. If the learning potential is the same, data from a generalized monitoring strategy may be useful for multiple applications. However, if significant differences occur, then monitoring strategies would need to be geared towards specific questions to avoid false conclusions.

3.2.2 Population and Microhabitat Data Collection

Given that sampling methods strongly impact the patterns observed in empirical data, we measured occupancy using the same methods specified by our model and during expert elicitation. Our experts described, our BN model predicted, and our field crew documented occupancy as measured by the Standardized North American Marsh Bird Monitoring Protocols (Conway 2008a; Appendix 3.1). Sample points were visited three times per breeding season (March through June), allowing 10-14 days to pass between visits. Two observers independently documented marsh bird responses to the call-back survey. The survey itself consisted of five minutes of silence followed by five 1-minute call-response intervals, each initiated by a different species' calls. The species sequence on our call-back recording was Black Rail (*Laterallus jamaicensis*), Least Bittern (*Ixobrychus exilis*), Virginia Rail (*Rallus limicola*), King Rail, and Common Moorhen (*Gallinula galeata*).

Following the call-back survey, the field crew measured vegetation, salinity, and water depth to characterize the site microhabitat conditions. These microhabitat features represented variables that experts believed strongly influenced King Rail nest site selection and daily habitat use within territories, but which are not easily represented in remotely-sensed map data. These data were collected to (1) compare the relative strength of microhabitat versus landscape data in models of King Rail occupancy, and (2) test whether proxy landscape variables effectively substituted for variation in microhabitat as intended. Each crew member sketched and visually estimated vegetation cover within a 30-m radius of the sample point, counting only species covering at least 1% of the 30-m circle. Unvegetated areas were also quantified and recorded as water or bare soil. With these data we calculated species richness (*rich*), presence of phragmites (*phrag*), percent cover of woody species (*woody*), presence of shrubs (*shrub*), and presence of marsh-water edge (*edge*). Measures of salinity (via refractometer) and water depth were made at the survey point and at 30 m from the survey point in each cardinal direction. For each site we calculated the mean depth (*depthX*), the standard deviation of depth (*depthSD*), and the mean salinity (*saltX*). Photographs taken towards the cardinal directions from the point center provided an archive of site condition and appearance for later reference.

3.2.3 Occupancy Models in PRESENCE

3.2.3.1 Detection Probability

In program PRESENCE, we estimated detection probability ($\hat{p}$) and probability of occupancy ($\hat{\Psi}$) conditional on detection. We combined data from 2008 and 2009 because we required estimates to reflect all variation in the data, yet not all plots were sampled both years, precluding year-specific analyses or use of a multi-season framework. Analyses were conducted in a single-species, single-season framework where encounter histories were in six columns. Columns 1-3 contained encounter histories of 2008, and columns 4-6 encounter histories of 2009. This model assumed that: 1) sites were "closed" to changes in occupancy within a season; 2) there were no false detections; and 3) detections across sites were independent (MacKenzie et al. 2006). We had designed the surveys to help meet these assumptions. We had conducted surveys every ten to twelve days (assumption 1). We trained observers before conducting surveys (assumption 2). We separated plots by at least 400 m (assumption 3). As noted above, however, we combined data from 2008 and 2009. Thus, we parameterized models to address between-year effects. We modeled detection probability as constant, year-specific, and sampling period by year (Table 3.1). The latter model structure accounted for within-season and between-year variation in detection, and had two parameterizations. One parameterization modeled all sampling periods separately by year (*YR*t*) whereas the other was similar except sampling occasions on the second year (2009) were modeled as constant (*YR*t4=t5=t6*). Next we determined whether there was a need to account for inter-annual differences in occupancy probability, because we wanted to know if we needed to have separate estimates of occupancy (*Psi(YR)*). This parameterization acknowledged that occupancy probability could change between years. Support for this parameterization was poor; a simpler model (*Psi(.)*) received greater support by the data. Finally, with the 2010 data, Rogers et al. (2013) modeled detection as constant, year specific, and by location (Table 3.1).

3.2.3.2 Detection-Adjusted Probability of Occupancy

Table 3.1. Detection probability (*p*) parameters. PRESENCE model notation and description for candidate models of King Rail detection probability.

The probability of detection…

Model Notation	**Parameter Description**
2008 & 2009 Models	
p(.)	… is constant.
p(*t*)	… depends of the survey period (t1, t2, t3, t4, t5, t6)
p(*YR*)	… depends on the year (2008, 2009)
p(*YR2*)	… depends on the year and the number of years visited (1,2)
p(*YR*t*)	… depends on the year and survey period
p(*YR*t4=t5=t6*)	… depends on survey period in 2008, but is equal across survey periods in 2009
2010 Models	
p(.)	… is constant.
p(*t*)	… depends of the survey period (t1, t2, t3)
p(*LOC*)	… depends on the location (Back Bay NWR & vicinity, Mackay Island NWR & vicinity)

We performed six analyses in PRESENCE (Table 3.2), all as single-species, single-season models with heterogeneous detection probability (MacKenzie et al. 2006). Each analysis incorporated a subset of the 24 possible variables (Table 3.3) as candidate models. The first three analyses compared univariate models arranged as (1) a set of all landscape variables (e.g., those calculated from spatial data layers), (2) a set of all microhabitat variables (e.g., those measured *in-situ*), and (3) all landscape and microhabitat variables together (Table 3.2: Micro Univariate, Land Univariate, and Land & Micro model sets). We evaluated the AIC weights of variables within each model to answer two questions:

- Did experts accurately identify the top ranking variables?
- Where landscape variables were selected to serve as proxy for a microhabitat variable, did the landscape and microhabitat provide comparable information value?

The fourth analysis evaluated a set of multivariate models that we defined to match expert hypotheses regarding patch access and nest site selection, as represented by the BN model structure (Table 3.2: Expert Hypotheses model set). Thus, where several predictor nodes led to an intermediate node, the associated set of predictor variables defined one candidate model. Where one variable could be represented either directly with empirically measured microhabitat data or indirectly with spatial landscape data, two candidate models were defined, one using the microhabitat data and the second using the landscape data. We evaluated the AIC weights of variables within each model to answer two questions:

- Did the information value of variables within the expert-defined BN (represented by the

Table 3.2. Summary of PRESENCE model sets. The PRESENCE models estimated detection-adjusted probability of occupancy based on call-response data. Model covariates included various combinations of landscape variables, site-specific microhabitat characteristics, the presence/absence of SEGAP Potential Habitat, and the time since the most recent prescribed burn.

		Response Variable: King Rail Observations		Covariates				
PRESENCE Model Set	Objectives	2008 & 2009	2010	2008 & 2009 Microhabitat Variables	2010 Microhabitat Variables	Landscape Variables	SEGAP Potential Habitat	Prescribed Burn Management History
Micro Univariate	• rank microhabitat variables to compare to expert rankings	x		x				
Land Univariate	• rank landscape variables to compare to expert rankings	x		x		x		
Land & Micro	• rank microhabitat versus landscape variables to compare to expert rankings • assess proxy variable relationships	x		x		x		
Expert Hypotheses	• rank landscape function units to compare to BBN variance reduction rankings	x				x		
Value of Perfect Information (VPI)	• identify the best model given all available data to update BBN • assess relative value of SEGAP data	x		x		x	x	
Rogers	• identify the best model given all available data to update BBN • assess relative value of management data		x		x	x		x

Table 3.3. Occupancy probability (Ψ) parameters. PRESENCE model notation and description for candidate models of King Rail site occupancy.

The probability of site occupancy…

Model Notation	Parameter Description
Ψ(.)	… is constant in space and time.
Microhabitat parameters	
Ψ(*rich*)	… depends on the number of emergent marsh species present (≥ 1% cover) within the survey plot.
Ψ(*phrag*)	… depends on the absence (< 1% cover) of *Phragmites australis* within the survey plot.
Ψ(*depthX*)	… depends on the mean water depth (15 measurements, five on each of three sampling occasions) within the survey plot.
Ψ(*depthSD*)	… depends on the variability (standard deviation) of water depth (15 measurements, five on each of three sampling occasions) within the survey plot.
Ψ(*woody*)	… depends on the percent cover of woody vegetation (trees and shrubs) within the survey plot.
Ψ(*shrub*)	… depends on the number of woody shrub species present (≥ 1% cover) within the survey plot.
Ψ(*edge*)	… depends on the presence (< 1% cover) of open water within the survey plot.
Ψ(*saltX*)	… depends on the mean salinity (15 measurements, five on each of three sampling occasions) within the survey plot.
Landscape parameters	
Ψ(*NDVI*)	… depends on the mean variability of the Normalized Difference Vegetation Index values within 250 m of the survey point. (standard deviation within 30 m radius on 1 m raster grid cell data)
Ψ(*SIZE*)	… depends on the size of the marsh patch containing the survey point.
Ψ(*CONNECT*)	… depends on the number of neighboring marsh patches within 250 m of the marsh patch containing the survey point.
Ψ(*WATER*)	… depends on the distance of the survey point from the nearest mapped open water.
Ψ(*EDGE*)	… depends on the number of marsh grid cells neighboring at least one water grid cell within 250 m of the survey point.
Ψ(*TYPE*)	… depends on the survey point falls in an interior (no marsh-water edge grid cells) or an edge marsh patch.
Ψ(*FETCH*)	… depends on whether or not the survey point falls in a marsh grid cell exposed to high wave energy and overwash.
Ψ(*SALT*)	… depends on the mapped marsh type (fresh/oligohaline, brackish/salt, or salt) at the survey point.
Ψ(*COV1*)	… depends on whether the majority land cover within 250 m of the survey point is marsh and water or non-marsh habitat classes.
Ψ(*ROADS*)	… depends on the distance of the survey point from the nearest road.
Ψ(*BOATS*)	… depends on the level of disturbance from boat traffic at the survey point.
Ψ(*HISTORY*)	… depends on documented history (presence/absence) of King Rail within a given distance (varies from 8 to 20 km depending on data source).
Other parameters	
Ψ(*NORTH*)	… depends on the location (north or south of Albemarle Sound)
Ψ(*LOC*)	… depends on the location (Back Bay NWR & vicinity, Mackay Island NWR & vicinity)
Ψ(*SEGAP*)	… depends on whether the survey point is Potential Habitat in SEGAP models
Ψ(*BURN*)	… depends on whether the survey site had been recently (<2 years) burned

variance reduction scores) accurately predict the explanatory power of the same variables and data within PRESENCE?

- Where a landscape variable served as proxy for a microhabitat variable, did the landscape and microhabitat provide comparable information value?

The fifth analysis explored the additive value of each step in the step-down modeling process (Table 3.1: Value of Perfect Information (VPI) model set). The VPI model set included as candidate models the original SEGAP Potential Habitat value (binary 0/1 score) alone and in combination with the top ranked (ΔAIC < 2.0) landscape and microhabitat models. Thus, we answered:

- What, if any, explanatory value is gained by eliciting expert knowledge and modeling occupancy at landscape-scales?

- What, if any, explanatory value is added by surveying occupancy and microhabitat features in the field?

For the sixth analysis we used data from Rogers et al. (2013). We created a model set that included the covariates from their top model (location and time since most recent prescribed burn) and our top VPI model (patch size and connectivity, shrub presence/absence, and whether the site had been modeled as Potential Habitat by SEGAP). Detection was modeled as a function of location (Back Bay *versus* Mackay Island vicinity), as determined by Rogers et al. (2013). We averaged the top models from this set to obtain the estimated occupancy conditional on detection history. By comparing estimates from this 2010 data and the 2008 and 2009 data (VPI model set), we answered:

- Do the models support similar conclusions regarding covariate value?

- Do the models generate similar expectations for the few sites that were surveyed in both studies?

3.2.4 Comparing the Bayesian Network and PRESENCE Predictions

PRESENCE models estimate occupancy given detection history and a suite of covariates. However, the resulting logistic equation can be applied to make predictions across the Ecoregional landscape spatial data, if we assume the observed detection probability and occupancy trends observed at the few points apply to all similar. To compare Ecoregional predictions of the expert-based BN to predictions of a data-only PRESENCE model, we chose to use the results of the Expert Hypotheses multivariate landscape models. For this comparison, we averaged the top models from this candidate set to generate a predictive equation for site estimates of Ψ that account for detection probability. We then applied this predictive equation to all marsh cells in the Ecoregional landscape. We used a paired t-test to compare the predicted values of the two models. This comparison does not validate the model, because it is a comparison of two independent models' predictions, rather than a comparison of predicted versus observed values. However, the comparison provides insight into expert knowledge and answered the questions:

- Do the expert- and data-driven models generate similar predictive landscapes?

- How is predictive uncertainty distributed across the landscape?

3.2.5 Updating the Bayesian Network

We updated the Condition Probability Tables in the Expert-Only BN model using the expectation maximization learning algorithm in Netica. This process presents the choice of (1) modifying the expert-defined probabilities based on the new data or (2) deleting the expert-defined probabilities and allowing the data to define the CPT values. We experimented with both methods, creating Expert+Data and Data-Only versions of the updated BNs (Table 3.4).

Table 3.4. Sources for values in the conditional probability tables. Comparison of data resources used in the original and updated versions of the Bayesian network models.

	Conditional Probability Table values defined with:		
	Expert	Data	
BN Model Name	Knowledge	2008 & 2009	2010
Expert-Only	x		
Expert+Data 0809	x	x	
Data-Only 0809		x	
Expert+Data 2010	x		x
Data-Only 2010			x

In this process, working with the 2008 and 2009 data, we first generated a table with the observed conditional occupancy from PRESENCE (Ψ) and data for the twelve landscape variables associated with each site for all 105 sites. This table was randomly split into a learning set (53 cases) and a testing set (52 cases). After first testing the Expert-Only model with the 52 test cases, we updated the model with the 53 learning cases, and then tested the updated model with the same 52 test cases. We repeated this process 30 times with different random draws and then compared the distribution of error rates for the Expert-Only and Expert+Data models. Then, using the same random draw sets, we repeated the process, but this time we discarded the expert-defined probabilities to create and test Data-Only BNs. Based on claims that BN models are well suited to adaptive management and learning, and concerns that our experts offered limited knowledge, we expected the updated models to have lower error rates than the original Expert-Only BN model.

The 2010 sample size was too small to use this single data resource in a test-update-retest cycle. Therefore, we used all data to update the model, creating 2010 versions of the Expert+Data and Data-Only models.

3.2.6 Validation of the Bayesian Network

We validated each BN model in two steps. First, we used a paired t-test to examine whether the BN occupancy predictions (Expert-Only, Expert+Data, and Data-Only models) matched the observed detection-adjusted occupancy as calculated in PRESENCE. For validation against 2008 and 2009 data, we used the conditional occupancy estimates from the VPI models. This model set indicated the top models given all available covariate data (landscape and microhabitat). Second, we used the Test-With-Cases function within Netica to explore the error structure of the BN models. This function compares BN predictions to observed values within an error matrix and reports the overall percentage error rate. We also assessed whether the expert-based BN models consistently over- or under-predicted occupancy relative to the PRESENCE estimates.

The 2010 call-back survey data provided an opportunity to validate our BN and PRESENCE models. In PRESENCE we created a model set that combined the Rogers et al. (2013) top model variables with our own (Table 3.2: Rogers). We averaged the top candidate models (ΔAIC < 2.0) from this new, combined model set to calculate the detection-adjusted occupancy estimate for each 2010 survey site. We then repeated the validation procedures outlined above to test the Expert-Only BN, Expert+0809Data BN, 0809Data-Only BN, and Expert Hypotheses PRESENCE model predictions. As these models all used landscape data, but incorporated both the expert-knowledge and data at different points and for different purposes, we could answer:

- Which model updating strategy provided the greatest gain in accuracy?

Importantly, the sampling strategy in the two studies differed. Our 2008 and 2009 sample sites had been roughly based upon a stratified random design that sampled across the full range of expected occupancy probabilities. The 2010 sample sites only occurred in habitat expected to offer high probability of occupancy (based on the Expert-Only model results). We were, therefore, able to explore the effect of sampling strategy on BN model updating by comparing three scenarios: (1) update with 50% of the 2008 and 2009 data, then validate with the remaining 50% 2008 and 2009 data; (2) update with all 2008 and 2009 data, then validate with 2010 data; and (3) update with all 2010 data, then validate with the 2008 and 2009 data. By comparing overall improvement in model accuracy and the structure of the error matrices, we answered:

- Do different sampling strategies result in different conclusions regarding model error?

- Is there any (dis)advantage to a monitoring strategy that focuses on sites where the animal is most likely to occur?

3.3 Results

3.3.1 King Rail Observations

3.3.1.1 2008 & 2009 Surveys

We surveyed 122 points in 2008 and 39 points in 2009 (Figure 3.1). Of the 39 points surveyed in 2009, nine had also been surveyed in 2008. Thus, the total number of geographically independent points surveyed was 152. Of the

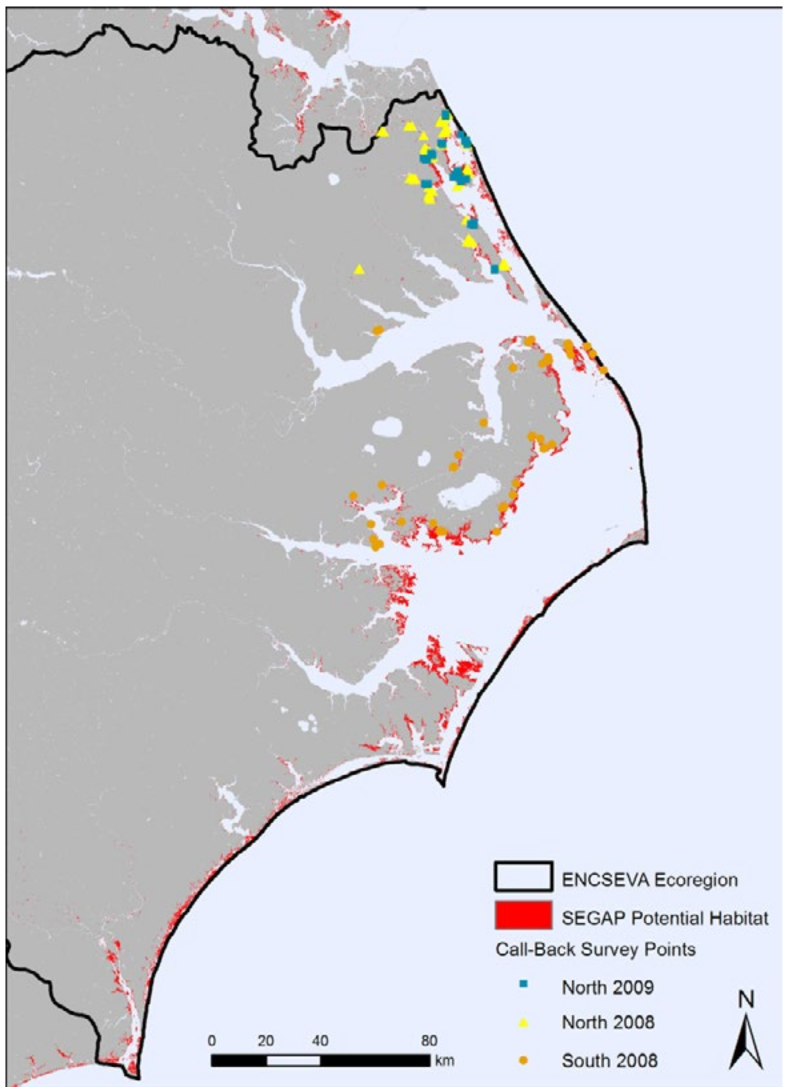


Figure 3.1. Validation survey points. Locations of call-back surveys conducted in 2008 and 2009 to validate and update the Bayesian network model.

2008 points, 23 had been surveyed to provide an accuracy assessment of the SEGAP land cover data and were not intended for occupancy or BN modeling.

Before occupancy modeling we removed (1) points surveyed for land cover accuracy assessment, plus (2) points mapped as marsh, but found to be non-marsh, (3) marsh points with a salinity greater than 15 ppt (to reduce chance of misidentifying Clapper Rail as King Rail), and points only surveyed once in a given year. Following this data preparation, 105 points remained for occupancy modeling in PRESENCE and BN model updating and validation. King Rail were detected at least once at 34 of the 105 surveyed marsh points, giving a naïve occupancy estimate (unadjusted for detection probability) of 0.324.

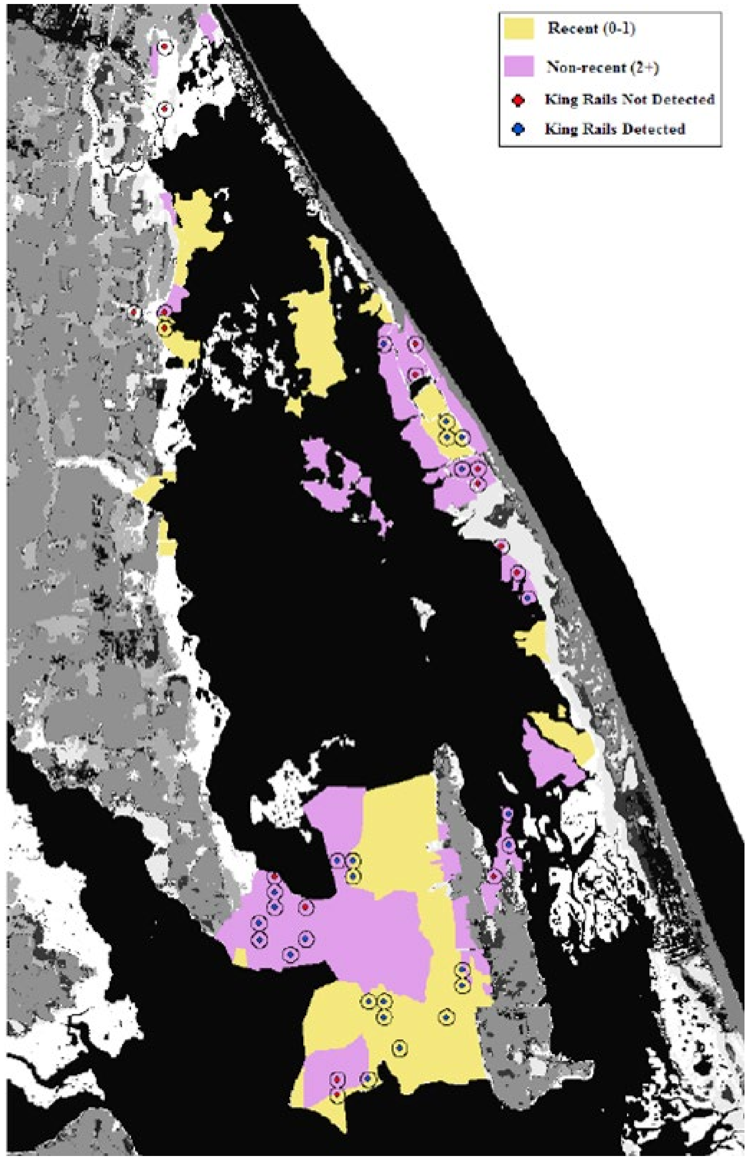


Figure 3.2. Sampling by Rogers in 2010. Figure 1.5 from Rogers (2011, used with permission): "Call-broadcast survey site locations and detections at Mackay Island NWR, Back Bay NWR and False Cape State Park during the 2010 breeding season. The study area is colored by recent (0-1 YSB) and non-recent (2 YSB) burns, and sites are colored by detections. Sites were selected from a systematic grid overlaying marsh habitat such that points were spaced 400 m apart. Sites are shown with 200 m buffers."

3.3.1.2 2010 Surveys

Rogers et al. (2013) surveyed 41 points in 2010 (Figure 3.2). All points were located in marsh habitat, so all were included in subsequent analyses. Three of these sites had been previously surveyed in 2008, eight in 2009, and a further three in both 2008 and 2009. They detected King Rail at least once at 25 of their sites, giving a naïve occupancy estimate of 0.610. They concluded that a model featuring location and fire history as site covariates with detection probability dependent upon location best explained variation in occupancy of King Rails (Rogers et al. 2013).

<u>3.3.2 Land Cover Accuracy Assessment</u>

Overall the SEGAP land cover maps accurately distinguished emergent marsh from non-marsh habitats (Table 3.5: Overall accuracy = 0.729). Type II errors (commission) were more common than Type I (omission) errors, so sensitivity (0.906) was higher than specificity (0.311) and the positive predictive value (0.756) was higher than the negative predictive value (0.583). In most omission errors, sites mapped as emergent marsh were observed to actually be open water (Table 3.6: 24 of 31 errors; 77%).

The SEGAP maps did not perform as well regarding classification of emergent marsh types based on salinity (Table 3.7). Although most emergent marsh had been mapped as Tidal Salt Marsh (79 of 127 marsh points; 62%), only two of these points had a salinity higher than 25 ppt and the remainder had a salinity less than 12 ppt. Before modeling we had noted that the region of Back Bay, an oligohaline coastal embayment, had been mapped as a salt water embayment, and we corrected this error manually. Our field observations supported our decision to reclassify the marshes around this embayment as Fresh and Oligohaline Tidal Marsh (see Figure 2.2). Our reclassification had no effect on the mean observed salinity of the Fresh and Oligohaline Tidal Marsh class, but increased the mean observed salinity of the Tidal Salt Marsh class from 4.7 ppt to 15.5 ppt (Table 3.7).

Table 3.5. Land cover error matrix: Marsh vs. Non-Marsh. Accuracy of emergent marsh versus non-marsh land cover classification was high (0.729). Errors of commission (mapping non-marsh as marsh) were more common than errors of omission (mapping marsh as non-marsh).

	Observed Land Cover		
Mapped Land Cover	Emergent Marsh	Non-Marsh	
Emergent Marsh	96	31	Positive Predictive Value = 0.756
Non-Marsh	10	14	Negative Predictive Value = 0.583
	Sensitivity = 0.906	Specificity = 0.311	**Overall Accuracy = 0.729**

Table 3.6. Distribution of classification errors among land cover classes at 151 sureyed sites. The most common error was the observation of open water where emergent marsh had been predicted.

	Observed Land Cover					
Mapped Land Cover	Agriculture, Grass, or Herbaceous	Developed or Bare	Emergent Marsh	Forest	Open Water	***Total***
Agriculture, Grassland, or Herbaceous	2			2		***4***
Developed or Bare		1	1	1		***3***
Emergent Marsh	5		96	2	24	***127***
Forest		1	6	1	3	***11***
Open Water	1		3		2	***6***
Total	***8***	***2***	***106***	***6***	***29***	***151***

3.3.3 PRESENCE Detection-Adjusted Occupancy Models

3.3.3.1 Detection Probability

We observed temporal trends in detection probability in the 2008 and 2009 data. Our 2008 season was exceptionally wet, while our 2009 season was exceptionally dry. Also, based on call

Table 3.7. Distribution of errors among marsh land cover classes. N = 133 sites classified as emergent marsh or open water. SEGAP further subdivides these coarse classes based on salinity. These classes and their expected values (ppt, parts per thousand) were Fresh (0 to 0.5 ppt), Oligohaline (0.5-5 ppt), Brackish (5-29 ppt), and Salt (≥30 ppt). High error in Tidal Salt Marsh class is due to misclassification of Back Bay region. Italicized text shows corrected values after manually reclassifying this region as Fresh and Oligohaline Tidal Marsh.

	Number	Mean (ppt)	SD
Open Water - Fresh	1	5.0	0.0
Tidal Freshwater Marsh	8	4.6	6.5
Fresh and Oligohaline Tidal Marsh	4	3.8	1.0
Fresh and Oligohaline Tidal Marsh	*77*	*3.8*	*2.2*
Open Water - Brackish/Salt	5	15.5	16.2
Salt and Brackish Tidal Marsh	36	12.4	6.9
Tidal Salt Marsh	79	4.7	4.6
Tidal Salt Marsh	*6*	*15.5*	*10.4*
Grand Total	133	6.9	6.7

Table 3.8. PRESENCE univariate microhabitat models. (A) The set of candidate microhabitat models for single season occupancy analysis ranked by their associated AIC values. The site covariates include eight microhabitat scale predictor variables. The covariates are evaluated as univariate models to facilitate comparison with expert variable ranks. All parameters are defined in Table 3.4. Competitive models (*ΔAIC* < 2.0) are identified in red text. The coefficient estimates for the top model are shown in (B).

(A) Microhabitat Univariate Model Set

Model	AIC	ΔAIC	AICw	Model Likelihood	Parameters	-2LogLikelihood
Ψ(*shrub*), p(*YR*t4=5=6*)	238.19	0	0.7641	1	6	226.19
Ψ(*woody*), p(*YR*t4=5=6*)	241.89	3.70	0.1200	0.1572	6	229.89
Ψ(*depthX*), p(YR*t4=5=6)	245.09	6.90	0.0242	0.0317	6	233.09
Ψ(*rich*), p(*YR*t4=5=6*)	245.46	7.27	0.0201	0.0264	6	233.46
Ψ(.), p(*YR*t4=5=6*)	245.47	7.28	0.0200	0.0263	5	235.47
Ψ(*North*), p(*YR*t4=5=6*)	246.53	8.34	0.0118	0.0155	6	234.53
Ψ(*depthSD*), p(*YR*t4=5=6*)	246.62	8.43	0.0113	0.0148	6	234.62
Ψ(*edge*), p(*YR*t4=5=6*)	247.04	8.85	0.0091	0.0120	6	235.04
Ψ(*saltX*), p(*YR*t4=5=6*)	247.37	9.18	0.0077	0.0102	6	235.37
Ψ(*phrag*), p(*YR*t4=5=6*)	247.42	9.23	0.0076	0.0099	6	235.42
Ψ(.), p(*YR*t*)	249.35	11.16	0.0029	0.0038	7	235.35
Ψ(.), p(*YR2*)	249.69	11.50	0.0024	0.0032	3	243.69
1 group, Constant P	270.82	32.63	0	0	2	266.82
Ψ(.), p(*YR*)	273.52	35.33	0	0	4	265.52

(B) Top Model Coefficient Estimates

Parameter	Beta (*β*)	SE
Intercept	1.588	0.813
shrub	-2.090	0.846

frequency, our first field season seemed to commence and end slightly later than the period of King Rail breeding. Field crew reported no King Rail calls during the third observation period of the first season, whereas in the second year, King Rail called throughout all survey periods. Therefore, detection probability was not constant across years and sampling periods. The temporal trend in detection was best represented as dependent on year and sampling period for year 2008, but constant for 2009 (*p[YR*t=4=5=6]*).

3.3.3.2 Univariate Model Sets to Explore Variable Ranking

The univariate model sets provided information about the relative value of the included variables to explain the observed occupancy patterns. The first model set evaluated occupancy in relation to observed microhabitat data (Table 3.8A). The model featuring shrub presence/absence (*shrub*) as the site covariate best explained occupancy of the study area by King Rail (AIC*w* = 0.76). None of the other microhabitat site covariates were competitive (all ΔAIC $\geq$ 3.7). Shrub presence had a negative relationship with King Rail occupancy (Table 3.8B; β= -2.09, SE = 0.85). Among our survey sites, shrub species richness ranged from 0 to 5 species within the 30 m radius vegetation survey area. The second model set evaluated occupancy in relation to the landscape metrics calculated from available spatial data (Table 3.9A). The model featuring patch size (*SIZE)*

Table 3.9.. PRESENCE univariate landscape models. (A) The set of candidate landscape models for single season occupancy analysis ranked by their associated AIC values. The site covariates include all landscape scale predictor variables, except the presence of boat traffic (*BOATS:* no data) and marsh patch type (*TYPE*: insufficient number of interior patches). All parameters are defined in Table 3.4. Competitive models (*ΔAIC* < 2.0) are identified in red text. The coefficient estimates for the top model are shown in (B).

(A) Landscape Univariate Model Set

Model	AIC	ΔAIC	AIC*w*	Model Likelihood	Parameters	-2LogLikelihood
Ψ(*SIZE*), *p*(*YR*t4=5=6*)	235.11	0	0.8288	1	6	223.11
Ψ(*FETCH*), *p*(*YR*t4=5=6*)	239.37	4.26	0.0985	0.1188	6	227.37
Ψ(*COV1*), *p*(*YR*t4=5=6*)	242.91	7.80	0.0168	0.0202	6	230.91
Ψ(*ROADS*), *p*(*YR*t4=5=6*)	243.17	8.06	0.0147	0.0178	6	231.17
Ψ(*CONNECT*), *p*(*YR*t4=5=6*)	243.56	8.45	0.0121	0.0146	6	231.56
Ψ(*WATER*), *p*(*YR*t4=5=6*)	243.66	8.55	0.0115	0.0139	6	231.66
Ψ(.), *p*(*YR*t4=5=6*)	245.47	10.36	0.0047	0.0056	5	235.47
Ψ(*EDGE*), *p*(*YR*t4=5=6*)	246.15	11.04	0.0033	0.0040	6	234.15
Ψ(*NORTH*), *p*(*YR*t4=5=6*)	246.76	11.65	0.0024	0.0030	6	234.76
Ψ(*SALT*), *p*(*YR*t4=5=6*)	246.88	11.77	0.0023	0.0028	6	234.88
Ψ(*NDVI*), *p*(*YR*t4=5=6*)	247.36	12.25	0.0018	0.0022	6	235.36
Ψ(*HIST*), *p*(*YR*t4=5=6*)	247.44	12.33	0.0017	0.0021	6	235.44
Ψ(.), *p*(*YR*t*)	249.35	14.24	0.0007	0.0008	7	235.35
Ψ(.), *p*(*YR2*)	249.69	14.58	0.0006	0.0007	3	243.69
1 group, Constant P	270.82	35.71	0	0	2	266.82
Ψ(.), *p*(*YR*)	273.52	38.41	0	0	4	265.52

(B) Top Model Coefficient Estimates

Parameter	Beta (*β*)	SE
Intercept	-0.006	0.369
SIZE	1.345	0.494

Table 3.10. PRESENCE univariate microhabitat and landscape models. The full set of all candidate landscape and microhabitat univariate models for single season occupancy analysis ranked by their associated AIC values. All parameters are defined in Table 3.4. Competitive models (*ΔAIC* < 2.0) are shown in red text. Top model coefficients are the same as those shown in Tables 3.8B.

Landscape & Microhabitat Univariate Model Set

Model	Expert Rank	AIC	ΔAIC	AICw	Model Likelihood	Parameters	-2LogLikelihood
Ψ(*SIZE*), *p*(*YR*t4=5=6*)	2	235.11	0	0.677	1	6	223.11
Ψ(*shrub*), *p*(*YR*t4=5=6*)	3	238.19	3.08	0.1451	0.2144	6	226.19
Ψ(*FETCH*), *p*(*YR*t4=5=6*)	6	239.37	4.26	0.0805	0.1188	6	227.37
Ψ(*woody*), *p*(*YR*t4=5=6*)	3	241.89	6.78	0.0228	0.0337	6	229.89
Ψ(*COV1*), *p*(*YR*t4=5=6*)	4	242.91	7.80	0.0137	0.0202	6	230.91
Ψ(*ROADS*), *p*(*YR*t4=5=6*)	5	243.17	8.06	0.0120	0.0178	6	231.17
Ψ(*CONNECT*), *p*(*YR*t4=5=6*)	2	243.56	8.45	0.0099	0.0146	6	231.56
Ψ(*WATER*), *p*(*YR*t4=5=6*)	3	243.66	8.55	0.0094	0.0139	6	231.66
Ψ(*depthX*), *p*(*YR*t4=5=6*)	1	245.09	9.98	0.0046	0.0068	6	233.09
Ψ(*rich*), *p*(*YR*t4=5=6*)	1	245.46	10.35	0.0038	0.0057	6	233.46
Ψ(.), *p*(*YR*t4=5=6*)	na	245.47	10.36	0.0038	0.0056	5	235.47
Ψ(*EDGE*), *p*(*YR*t4=5=6*)	3	246.15	11.04	0.0027	0.0040	6	234.15
Ψ(*depthSD*), *p*(*YR*t4=5=6*)	6	246.62	11.51	0.0021	0.0032	6	234.62
Ψ(*North*), *p*(*YR*t4=5=6*)	na	246.83	11.72	0.0019	0.0029	6	234.83
Ψ(*SALT*), *p*(*YR*t4=5=6*)	4	246.88	11.77	0.0019	0.0028	6	234.88
Ψ(*edge*), *p*(*YR*t4=5=6*)	3	247.04	11.93	0.0017	0.0026	6	235.04
Ψ(*NDVI*), *p*(*YR*t4=5=6*)	1	247.36	12.25	0.0015	0.0022	6	235.36
Ψ(*saltX*), *p*(*YR*t4=5=6*)	4	247.37	12.26	0.0015	0.0022	6	235.37
Ψ(*phrag*), *p*(*YR*t4=5=6*)	1	247.42	12.31	0.0014	0.0021	6	235.42
Ψ(*HIST*), *p*(*YR*t4=5=6*)	na	247.44	12.33	0.0014	0.0021	6	235.44
Ψ(.), *p*(*YR*t*)	na	249.35	14.24	0.0005	0.0008	7	235.35
Ψ(.), *p*(*YR2*)	na	249.69	14.58	0.0005	0.0007	3	243.69
1 group, Constant P	na	270.82	35.71	0	0	2	266.82
Ψ(.),p(YR)	na	273.52	38.41	0	0	4	265.52

best explained occupancy of the study area by King Rail (AIC*w* = 0.83). None of the other landscape metric models were competitive relative to the *SIZE* model (all ΔAIC ≥ 4.26). Patch size (β = 1.35, SE = 0.49) was positively correlated with King Rail occupancy (Table 3.9B). Patch size in the Ecoregion ranged from 0.09 ha to 2,422 ha with a median of 100 ha. The third model set included all microhabitat and landscape metrics calculated from available spatial data (Table 3.10). As expected based on the previous model sets, the *SIZE* (AIC*w* = 0.68) and *shrub* (AIC*w* = 0.15) models were the top two performing models. The *shrub* model (ΔAIC = 3.08), however, was not competitive relative to the *SIZE* model.

In general, the rank order of variables in the occupancy models differed from experts' predictions. None of the experts' top-ranked variables achieved a ΔAIC ≥ 2.0 when examined as univariate parameters within PRESENCE (Table 3.10). Experts' expectation that microhabitat variables would outperform landscape variables was not supported by the data collected in this study. Of the landscape variables, experts did correctly identify patch size (*SIZE*) as an important explanatory variable.

Only three variables (salinity, marsh-water edge, and vegetation diversity) were represented at both the microhabitat and landscape scales. If the landscape metrics selected served as strong proxy data for the microhabitat conditions, we expected the model pairs to have similar AIC scores (Table 3.10) and the field observations and landscape metric data to be strongly correlated. Differences between AIC values were least for *SALT* and *saltx* (0.49) and greatest for *NDVI* and *rich* (1.90).

However, all non-competitive models had very similar AIC values. A simple linear regression measured no correlation between the NDVI diversity metric (*NDVI*) as calculated from aerial imagery and vegetation richness (*rich*) as measured in the field (R^2=0.02). A logistic regression measured no correlation between the presence/absence of edge (*edge*) in field survey plots and the number of marsh-water edge cells (*EDGE*) mapped in land cover data for the same location (R^2=0.001). Field salinity measures (*saltX*), however, matched mapped Fresh-Oligohaline versus Brackish cover classifications (*SALT*; following correction of the Back Bay region's land cover classification). After averaging the 2008 and 2009 *saltX* values, a one-tailed Student's t-test assuming unequal variance indicated that the mean salinity of the marshes mapped as Brackish ($\bar{X}$ = 6.5; SD = 3.9) was higher ($p < 0.001$) than the mean salinity measured in the marshes mapped as Fresh-Oligohaline ($\bar{X}$ = 2.9; SD = 2.1).

Table 3.11. PRESENCE expert hypotheses models. The full set of candidate multivariate models for single season occupancy analysis ranked by their associated AIC values. All parameters are defined in Table 3.4. Competitive models (ΔAIC < 2.0) are identified in red text. The coefficient estimates for the top model are shown in (B).

Model	AIC	ΔAIC	AICw	Model Likelihood	Parameters	-2Log Likelihood
Ψ(*SIZE*CONNECT*), *p*(*YR*t4=5=6*)	233.87	0	0.4586	1	8	217.87
Ψ(*SIZE*), *p*(*YR*t4=5=6*)	235.11	1.24	0.2467	0.5379	6	223.11
Ψ(*SIZE*CONNECT+HIST*), *p*(*YR*t4=5=6*)	235.31	1.44	0.2232	0.4868	9	217.31
Ψ(*WATER+shrub+saltX*), *p*(*YR*t4=5=6*)	240.24	6.37	0.0190	0.0414	8	224.24
Ψ(*FETCH+edge*), *p*(*YR*t4=5=6*)	241.11	7.24	0.0123	0.0268	7	227.11
Ψ(*COV1+ROADS*), *p*(*YR*t4=5=6*)	241.15	7.28	0.0120	0.0263	7	227.15
Ψ(*WATER+shrub+SALT*), *p*(*YR*t4=5=6*)	241.31	7.44	0.0111	0.0242	8	225.31
Ψ(*FETCH+EDGE*), *p*(*YR*t4=5=6*)	241.34	7.47	0.0109	0.0239	7	227.34
Ψ(*WATER+rich+SALT*), *p*(*YR*t4=5=6*)	244.47	10.60	0.0023	0.0050	8	228.47
Ψ(*WATER+rich+saltX*), *p*(*YR*t4=5=6*)	245.45	11.58	0.0014	0.0031	8	229.45
Ψ(.), *p*(*YR*t4=5=6*)	245.47	11.60	0.0014	0.0030	5	235.47
Ψ(*WATER+NDVI+saltX*), *p*(*YR*t4=5=6*)	246.44	12.57	0.0009	0.0019	8	230.44
Ψ(*north*), *p*(*YR*t4=5=6*)	246.83	12.96	0.0007	0.0015	6	234.83
Ψ(*WATER+NDVI+SALT*), *p*(*YR*t4=5=6*)	247.44	13.57	0.0005	0.0011	8	231.44
Ψ(.), *p*(*YR*t*)	249.35	15.48	0.0002	0.0004	7	235.35
Ψ(.), *p*(*YR2*)	249.69	15.82	0.0002	0.0004	3	243.69
1 group, Constant P	270.82	36.95	0	0	2	266.82
Ψ(.),p(YR)	273.52	39.65	0	0	4	265.52

(B) Top Model Average Coefficient Estimates

Parameter	Beta (β)	SE
Intercept	0.497	0.642
*SIZE*CONNECT*	-6.761	5.781
SIZE	3.081	1.609
CONNECT	1.150	1.019
HIST	0	0.171

3.3.3.3 PRESENCE Predictive Landscape Model

The fourth set of PRESENCE models (Table 3.11) evaluated occupancy in relation to expert hypotheses as reflected by the BN model structure. Three models were competitive (ΔAIC < 2.0). These were the models featuring a patch size and connectivity interaction (*SIZE*CONNECT*; AIC*w* = 0.46), patch size alone (*SIZE*; AIC*w* = 0.26) and the interaction with an added term to account for past site occupancy (*SIZE*CONNECT+HIST*; AIC*w* = 0.22). Although we included both landscape and microhabitat versions of each model where either scale of data could apply (e.g., amount of edge, salinity, and vegetation diversity), no other model was competitive regardless of the scale considered (all ΔAIC ≥ 6.37). Averaging the top three models resulted in a weakly predictive model equation, where each coefficient estimate had large standard errors (Table 3.11B). While patch size had a positive relationship with King Rail occupancy (β= 3.76, SE = 1.61), both connectivity and history seemed to have no relationship (*CONNECT* β= 1.15, SE = 1.02; *HIST* β= 0, SE = 0.17). The interaction between size and connectivity had a negative relationship with King Rail occupancy (β= -6.76, SE = 5.78).

The top models in this set incorporated those variables that experts hypothesized to influence patch access. Variable combinations associated with site selection for nesting, foraging, or avoiding disturbance were all non-competitive. This pattern generally concurred with rankings by variance reduction scores within the BN, where the access node (VR = 0.0203) scored higher than any of the site selection nodes (VR = 0.0088 to 0.0002).

Table 3.12. PRESENCE value of perfect information models. The full set of candidate multivariate models for single season occupancy analysis ranked by their associated AIC values. All parameters are defined in Table 3.4. Competitive models (ΔAIC < 2.0) are identified in red text. The coefficient estimates for the top model are shown in (B).

Model	AIC	ΔAIC	AICw	Model Likelihood	Parameters	-2Log Likelihood
Ψ(SEGAP+*SIZE*CONNECT*+*shrub*), *p*(*YR*t4=5=6*)	220.33	0	0.8177	1	10	200.33
Ψ(SEGAP+*SIZE*CONNECT*), *p*(*YR*t4=5=6*)	223.93	3.60	0.1352	0.1653	9	205.93
Ψ(SEGAP+*shrub*), *p*(*YR*t4=5=6*)	226.73	6.40	0.0333	0.0408	7	212.73
Ψ(*SIZE*CONNECT*+*shrub*), *p*(*YR*t4=5=6*)	229.97	9.64	0.0066	0.0081	9	211.97
Ψ(*SIZE*CONNECT*), *p*(*YR*t4=5=6*)	230.60	10.27	0.0048	0.0059	8	214.60
Ψ(*SEGAP*), *p*(*YR*t4=5=6*)	232.11	11.78	0.0023	0.0028	6	220.11
Ψ(*shrub*), *p*(*YR*t4=5=6*)	238.19	17.86	0.0001	0.0001	6	226.19
Ψ(.), *p*(*YR*t4=5=6*)	245.47	25.14	0	0	5	235.47
Ψ(*north*), *p*(*YR*t4=5=6*)	246.76	26.43	0	0	6	234.76
Ψ(.), *p*(*YR*t*)	249.35	29.02	0	0	7	235.35
Ψ(.), *p*(*YR2*)	249.69	29.36	0	0	3	243.69
1 group, Constant P	270.82	50.49	0	0	2	266.82
Ψ(.),p(YR)	273.52	53.19	0	0	4	265.52

(B) Top Model Average Coefficient Estimates

Parameter	Beta (β)	SE
Intercept	-2.706	1.343
SEGAP	3.348	1.315
*SIZE*CONNECT*	-13.964	6.562
SIZE	4.731	2.049
CONNECT	2.400	1.384
shrub	1.902	0.954

Table 3.13. PRESENCE Rogers models. The full set of candidate multivariate models for single season occupancy analysis ranked by their associated AIC values. All parameters are defined in Table 3.4. Competitive models (*ΔAIC* < 2.0) are identified in red text. The coefficient estimates for the top model are shown in (B).

Model	AIC	ΔAIC	AICw	Model Likelihood	Parameters	-2Log Likelihood
Ψ(*LOC+BURN*), *p*(*LOC*)	134.58	0	0.3198	1	5	124.58
Ψ(*SIZE*CONNECT+BURN*), *p*(*LOC*)	135.51	0.93	0.2009	0.6281	7	121.51
Ψ(*BURN+shrub+LOC*), *p*(*LOC*)	136.33	1.75	0.1333	0.4169	6	124.33
Ψ(*SIZE*CONNECT+shrub*), *p*(*LOC*)	136.33	2.05	0.1148	0.3588	8	120.63
Ψ(*SIZE*CONNECT+BURN+shrub*), *p*(*LOC*)	137.10	2.52	0.0907	0.2837	8	121.10
Ψ(*SIZE*CONNECT+shrub+LOC*), *p*(*LOC*)	138.63	4.05	0.0422	0.1320	8	122.63
Ψ(*SIZE*CONNECT+LOC*), *p*(*LOC*)	139.56	4.98	0.0265	0.0829	7	125.56
Ψ(*LOC+shrub*), *p*(*LOC*)	139.74	5.16	0.0242	0.0758	5	129.74
Ψ(*BURN+shrub*), *p*(*LOC*)	139.82	5.24	0.0233	0.0728	5	129.82
Ψ(*SIZE*CONNECT+SEGAP+shrub*), *p*(*LOC*)	141.23	6.65	0.0115	0.0360	8	125.23
Ψ(.), *p*(*LOC*)	142.37	7.79	0.0065	0.0203	3	136.37
1 group, Constant P	142.85	8.27	0.0051	0.0160	2	138.85
Ψ(.),p(*t*)	145.93	11.35	0.0011	0.0034	4	137.93

(B) Top Model Average Coefficient Estimates

Parameter	Beta (*β*)	SE
Intercept	-0.7704	0.8151
LOC	1.3016	1.1068
BURN	2.0962	1.0732
*SIZE*CONNECT*	-1.8224	3.6074
SIZE	1.7285	2.7063
CONNECT	0.4384	0.7895
shrub	0.026	0.0753

3.3.3.4 Conditional Occupancy Estimates

Based on 2008 and 2009 data, the VPI model set evaluated the relative value of the SEGAP potential habitat designation, the landscape data, and the microhabitat data, alone and in combination, to explain observed occupancy patterns (Table 3.12). The model with all available information received the greatest weight (AIC*w* = 0.82) and no other model was competitive with this top model (all ΔAIC ≥ 3.60). Considering the rank order of the models, models incorporating the SEGAP potential habitat data (*SEGAP*) generally outperformed models without this variable. Models excluding landscape data (*SEGAP+shrub* and *shrub*) generally performed poorly relative to models excluding microhabitat data (*SEGAP+SIZE*CONNECT* and

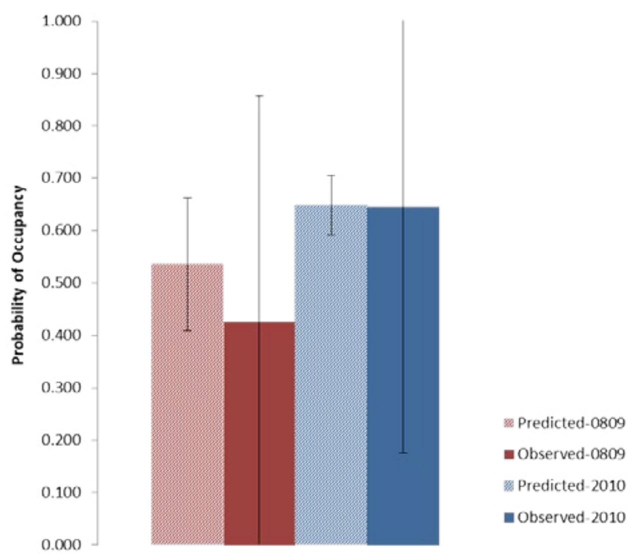


Figure 3.3. Observed versus predicted probability of occupancy by King Rail. Predicted values were calculated by the Expert-Only BN model. The observed values were calculated with the top fitting PRESENCE model for the given data set. Thus the 2008 and 2009 observed values were calculated with the VPI PRESENCE model and the 2010 observed values were calculated with the Rogers PRESENCE model.

*SIZE*CONNECT*).

Based on 2010 data, the Rogers model set (Table 3.13) evaluated the same parameters as the VPI set but with the addition of their project's top covariates: location and burn history. The three competitive models in the Rogers set included location (*LOC*), landscape characteristics (*SIZE*, *CONNECT*), microhabitat characteristics (*shrub*), management history (*BURN*), but not the SEGAP potential habitat designation (*SEGAP*). The model that had been top in the VPI set fell to tenth position (ΔAIC = 6.65) when the new covariates were considered. Although several covariates were included in the top models, the standard errors exceeded the value of the beta coefficients for all but two of the covariates (Table 3.13: *LOC* β = 1.30, SE = 1.11; *BURN* β = 2.10, SE = 1.07).

Table 3.14 Comparison of errors under two sampling strategies. Distribution of errors among three categories: Low, Moderate, and High probability of occupancy for two sets of data. In 2008 and 2009 sites predicted to be Low, Moderate, and High were targeted for observation. In 2010, sampling focused on sites predicted to have High probability of occupancy. In both years observations indicate very few Moderate sites.

2008-09			Predicted
Observed	Low	Moderate	High
Low	13	29	17
Moderate	1	3	5
High	3	8	26

2010			Predicted
Observed	Low	Moderate	High
Low	0	0	14
Moderate	0	0	0
High	0	1	23

Probability Categories:
Low = 0.0 – 0.33; Moderate = 0.33 – 0.66; High = 0.66 – 1.0

Table 3.15 Distribution of errors among two categories: probably Unoccupied and Occupied. This classification system eliminates the large error associated with Moderate sites (frequently predicted, never observed). Not surprisingly, accuracy rates increase as the number of categories decreases.

Predicted	**Observed**	
Expert-Only	Unoccupied	Occupied
Unoccupied	17	6
Occupied	15	15
Expert+Data 0809	Unoccupied	Occupied
Unoccupied	27	11
Occupied	5	10
Data-Only 0809	Unoccupied	Occupied
Unoccupied	26	11
Occupied	6	10

Probability Categories:
Unoccupied = 0.0 – 0.5; Occupied = 0.5 – 1.0

3.3.4 Bayesian Network Updating and Validation Cycle

3.3.4.1 Expert-Only Model Validation

The distribution of probability values differed markedly between the Expert-Only BN predictions and conditional-occupancy observations (Figure 3.3). For the 105 sites visited in 2008 and 2009, the values predicted by the Expert-Only model approximated a normal distribution ($\bar{X}$ = 0.536, median = 0.558, SD = 0.126), but the observed psi-conditional values from the VPI model were negatively skewed and over-dispersed ($\bar{X}$ = 0.427, median = 0.184, SD = 0.432). In both data sets, the Expert-Only model was overly optimistic; the probability of occupancy was over-estimated far more frequently than it was under-estimated (Table 3.14: ratio = 51:12 in 2008 and 2009). Pair-wise t-test of the predicted values versus the VPI psi-conditional values rejected the null hypothesis of equality (two-tailed test, α = 0.05, p = 0.006). The 2010 surveys had primarily targeted sites with a high probability of King Rail occupancy. The experts' tendency to over-prediction was again seen within the 2010 data; King Rail were not detected at 14 of 23 sites that had been predicted to have high (≥ 0.66) probability of occupancy (Table 3.14). Accordingly, although the predicted and observed occupancy values for the 38 sites visited in 2010 shared similar means (predicted $\bar{X} \approx$ observed $\bar{X} = 0.65$), the observed data were much more widely dispersed (predicted SD = 0.06; observed SD = 0.47).

Not surprisingly, error rates were highly dependent upon the number of categories defined for the response variable. The greater the number of categories defined, the higher the overall percentage error. The overall error rate of the Expert-Only BN model in 2008 and 2009 was 60% if evaluated with three categories (Table 3.14: High, Moderate, Low), but only 37.8% if measured with two categories (Table 3.15: Occupied, Unoccupied). This error pattern reflects a difference between the two modeling approaches. The majority of expert predictions fall in the Moderate category, while the majority of VPI observations, and therefore the PRESENCE models, fall in the High or Low category. Throughout the remainder of this report, error rates refer to assessment with the binary categories.

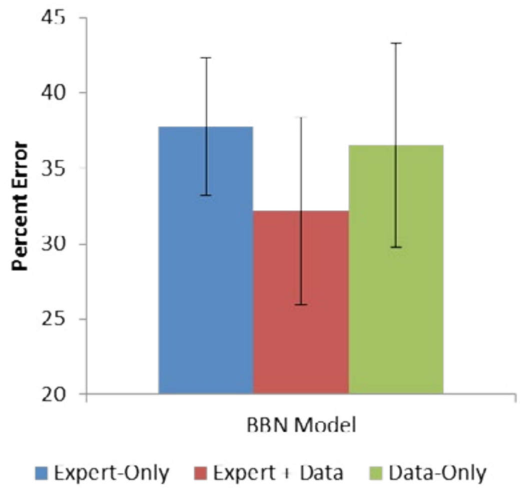


Figure 3.4. Overall percent error before and after updating the models with data. Results of two alternative update methods are illustrated: (1) the Expert+Data model incorporates the expert-defined conditional probability values, but (2) the Data-Only model discards the expert-defined values prior to updating. The percent error values are the overall error calculated from the confusion matrices comparing BN predictions to observed Psi-Conditional values from the top VPI PRESENCE model.

3.3.4.2 Expert+Data and Data-Only Models

In this case study, the combination of expert-knowledge with empirical data consistently provided the greatest predictive accuracy. Based on updating and testing with random draws from the 2008 and 2009 data, this learning process did reduce the overall error rates (Figure 3.4: $\bar{X}$ of Expert-Only 37.8%, Expert+Data 32.8%, Data-Only 36.0%). Based on results of paired t-tests, this reduction was only significant when expert-defined conditional probability tables were adjusted by available empirical data ($p < 0.000$, $\alpha = 0.05$, one-tailed), not when this aspect of the expert knowledge was discarded ($p = 0.224$, $\alpha = 0.05$, one-tailed). Error of the Data-Only versions of the updated models exceeded the error of the Expert+Data models in all cases (Table 3.16). Updating the models changed the structure of the model error. While model error in the Expert-Only model was primarily due to false positives, predictions by the updated models resulted in a higher proportion of false negatives (Table 3.16).

3.3.4.3 Stratified Random versus Non-Random Data

Testing the Expert-Only models with the stratified random (2008 and 2009) and non-random (2010) data produced similar overall error rates (Table 3.16, A & B). However, the non-random data only sampled sites predicted to be occupied; the test provides no information about the accuracy of

Table 3.16. Comparison of error rates for all models. The overall percentage error and error structure is shown for all models. The table notes which data were used to update the conditional probability tables and which data were used to test the original and the updated versions of the models. The effects of sampling strategy are compared (A *vs*. B). The effects of discarding versus keeping expert-based CPT values prior to learning are compared (C *vs*. D; E *vs*. F; G *vs*. H). The effects of a data-driven versus expert-driven modeling approach are compared (I *vs*. all other models). We included two example management scenarios to illustrate the ramifications of model error and learning on the ability to make sound management decisions.

		ERROR STRUCTURE				EXAMPLE OF ERROR IMPLICATIONS TO MANAGEMENT DECISIONS	
	OVERALL PERCENT ERROR	**True Positive** (Predicted Occupancy & Observed Occupancy)	**True Negative** (Predicted Unoccupied & Observed Unoccupied)	**False Positive** (Predicted Occupancy & Observed Unoccupied)	**False Negative** (Predicted Unoccupied & Observed Occupancy)	I purchase an acre of habitat predicted to have KIRA, what's the chance I failed to protect any KIRA?	I flooded an acre predicted to be unoccupied, what's the chance I accidentally displace a KIRA ?
Original BN model							
A **Expert-Only** (tested with 2008&9)	**39.05**	32	32	33	8	0.51	0.20
B **Expert-Only** (tested with 2010)	**36.84**	24	0	14	0	0.37	na
BN updated with random draw from 2008 & 2009 data, then tested with remaining data (mean, SD)							
C **Expert + Data**	**32.8 (5.9)**	9.4 (2.5)	26.0 (2.9)	6.3 (3.6)	11.1 (4.5)	0.38 (0.10)	0.29 (0.08)
D **Data-Only**	**36 (6.5)**	9.1 (3.3)	24.7 (3.1)	7.7 (3.3)	11.5 (4.3)	0.46 (0.12)	0.31 (0.08)
BN updated with 2008 & 2009 data, then tested with 2010 data							
E **Expert + Data**	**31.58**	21	5	9	1	0.30	0.17
F **Data-Only**	**34.21**	22	3	11	2	0.33	0.40
BN updated with 2010 data, then tested with 2008 & 2009 data							
G **Expert + Data**	**30.48**	23	50	15	17	0.39	0.25
H **Data-Only**	**40.00**	23	40	25	17	0.52	0.30
Top VPI Model (with landscape data only), tested with 2010 data							
I **PRESENCE model**	**39.47**	22	1	13	2	0.37	0.67

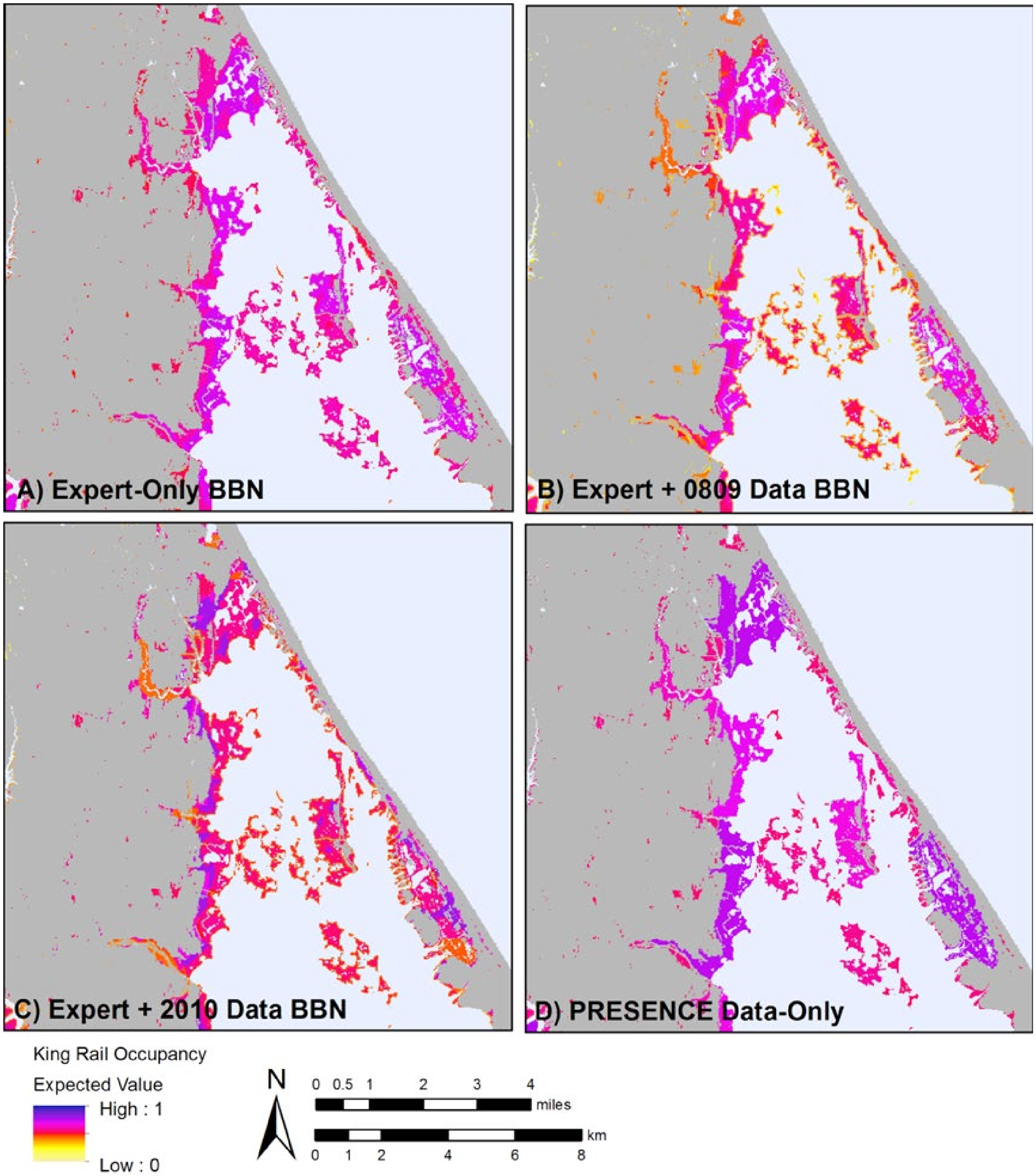


Figure 3.5. Comparison of four predictions: Back Bay Area. Predicted probability of King Rail occupancy in vicinity of Back Bay National Wildlife Refuge and False Cape State Park. The four predictions are (A) the original BN model constructed solely from expert knowledge, (B) the BN model updated with data collected across all occupancy categories (Low, Moderate, and High), (C) the BN model updated with data collected only from site predicted to be occupied (High and Moderate), and (D) the extrapolation of the top PRESENCE model equation across the Ecoregional landscape.

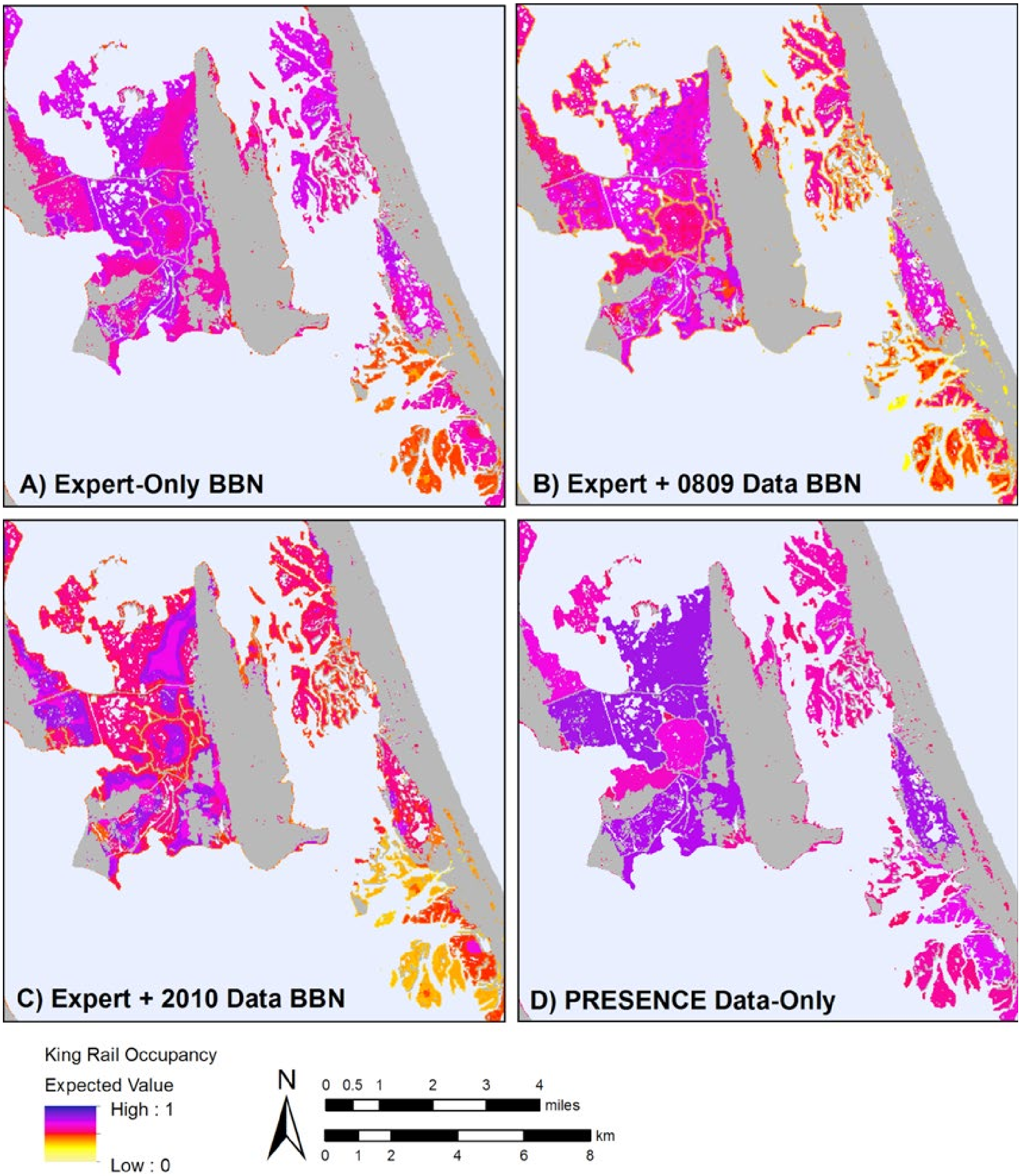


Figure 3.6. Comparison of four predictions: Mackay Island Area. Predicted probability of King Rail occupancy in vicinity of Mackay Island and Currituck National Wildlife Refuges. The four predictions are (A) the original BN model constructed solely from expert knowledge, (B) the BN model updated with data collected across all occupancy categories (Low, Moderate, and High), (C) the BN model updated with data collected only from site predicted to be occupied (High and Moderate), and (D) the extrapolation of the top PRESENCE model equation across the Ecoregional landscape.

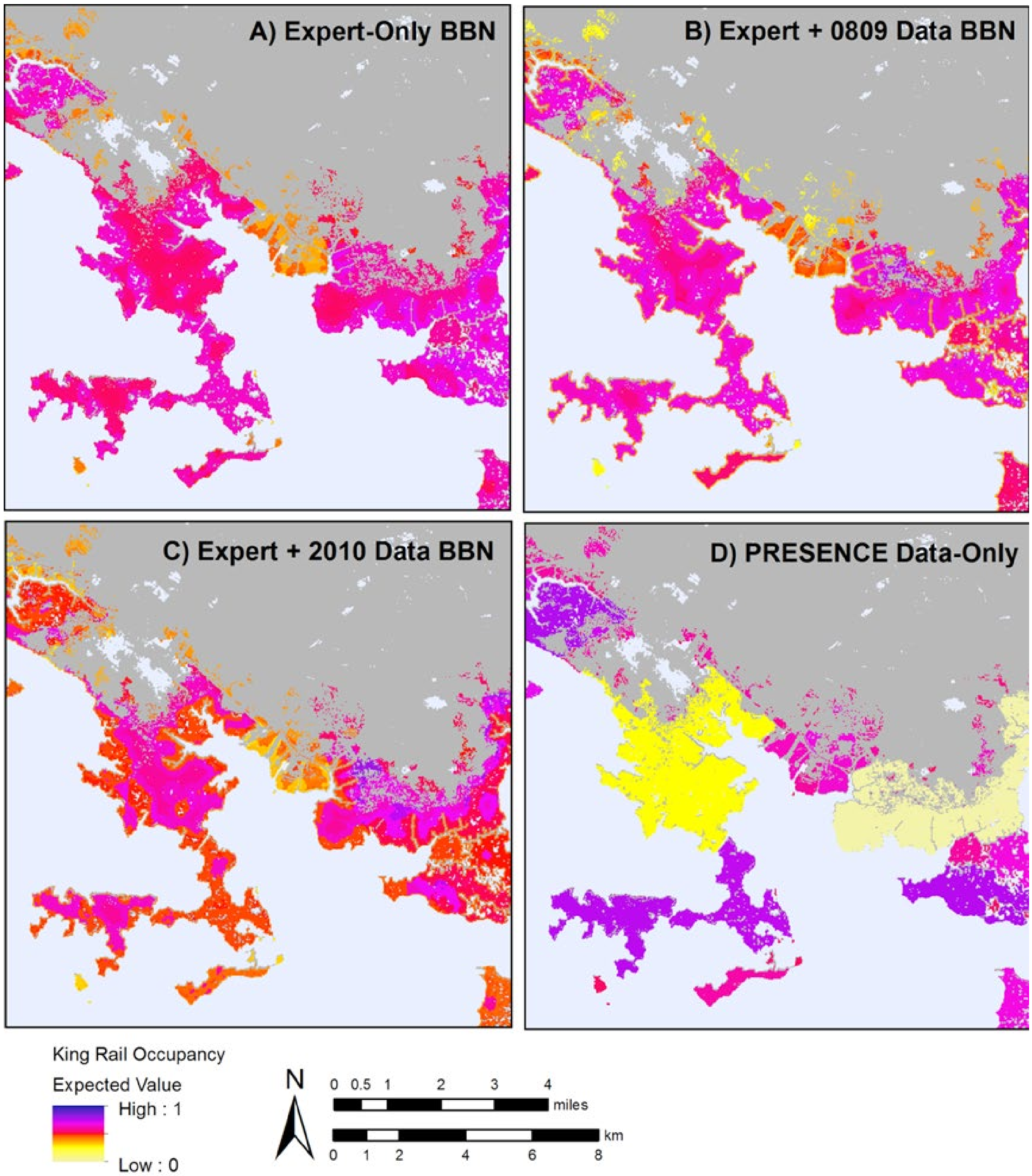


Figure 3.7. Comparison of four predictions: Swanquarter Area. Predicted probability of King Rail occupancy in vicinity of Swanquarter National Wildlife Refuges. The four predictions are (A) the original BN model constructed solely from expert knowledge, (B) the BN model updated with data collected across all occupancy categories (Low, Moderate, and High), (C) the BN model updated with data collected only from site predicted to be occupied (High and Moderate), and (D) the extrapolation of the top PRESENCE model equation across the Ecoregional landscape.

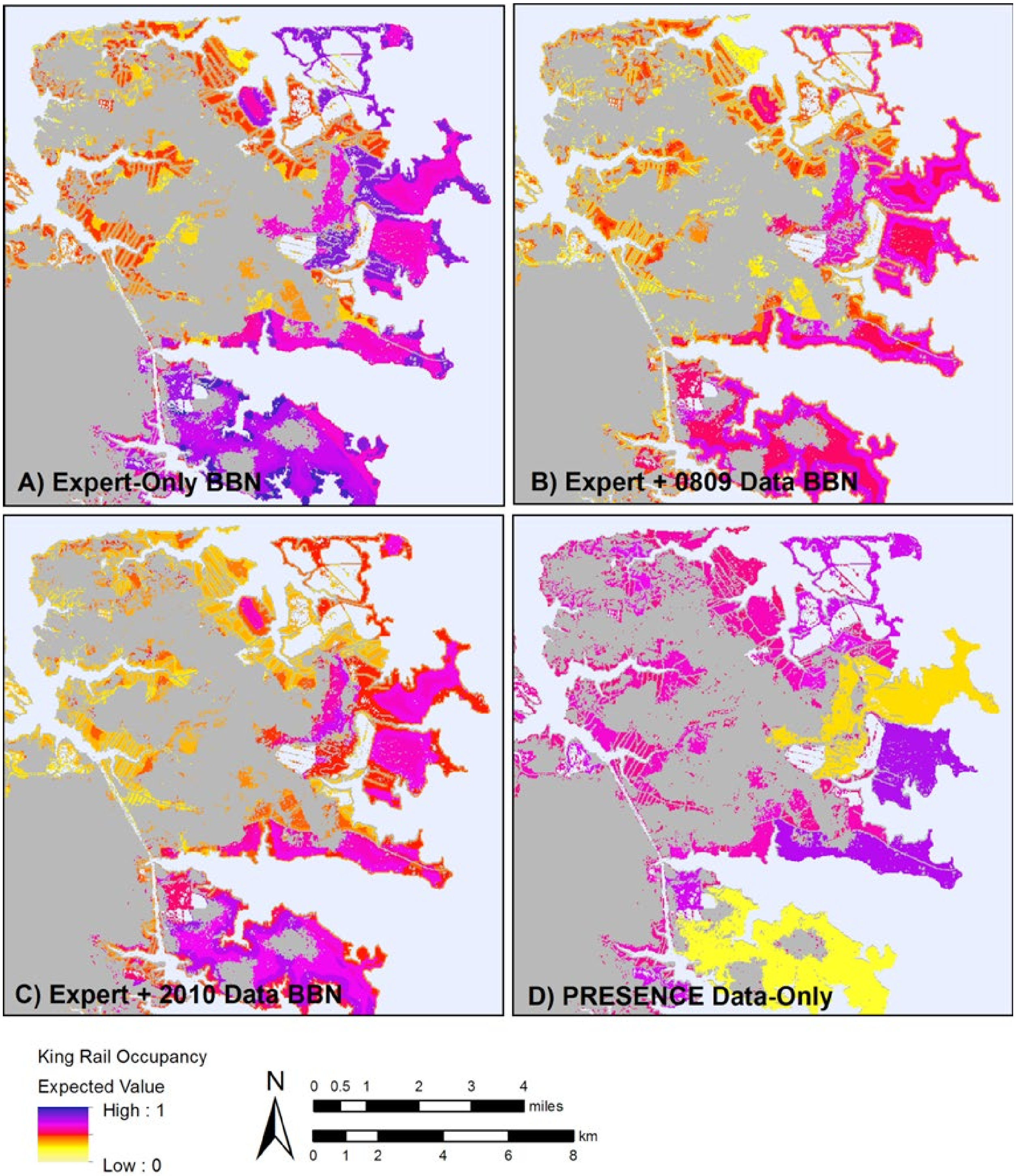


Figure 3.8 Comparison of four predictions: Hobucken Area. Predicted probability of King Rail occupancy in vicinity of Hobucken, North Carolina. The four predictions are (A) the original BN model constructed solely from expert knowledge, (B) the BN model updated with data collected across all occupancy categories (Low, Moderate, and High), (C) the BN model updated with data collected only from site predicted to be occupied (High and Moderate), and (D) the extrapolation of the top PRESENCE model equation across the Ecoregional landscape.

negative predictions. Models updated with half (Table 3.16 C & D) or all (Table 3.16, E & F) of the 2008 and 2009 data, also presented similar error rates whether tested with the remaining 2008 and 2009 data or the 2010 data. As only a single value is generated for each model, it is impossible to state whether these differences are significant. Grubb's test (two-tailed, $\alpha = 0.05$) identified the Expert+Data model as the most extreme value, however, none of the values are outliers from the set.

3.3.4.4 Expert-Driven versus Data-Driven Models

Given two years of empirical occupancy data and available spatial data, the top PRESENCE model predicted 2010 observations with higher error rates than any of the BN models (Table 3.16 B, E, F, & I).

3.3.5 Comparison of Spatially Explicit Predictions

Our cycles of model creation and updating resulted in four distinct spatially-explicit predictions of King Rail occupancy within the Ecoregion (Figures 3.5-3.8). In some regions, such as Back Bay (Figure 3.5), the greatest similarity is seen between the Expert-Only BN and the PRESENCE model. In other regions, such as Hobucken (Figure 3.8), the three BN models generally resemble one another, yet are distinct from the PRESENCE model. The PRESENCE model presents less spatial diversity in the prediction values, because the top model only included two patch characteristics (size and connectivity) to score each raster cell. The site level detail which allows variation within patches is only included in the BN models.

The proportion of habitat falling in each occupancy category (Low, Moderate, or High) and the amount of occupied habitat in conservation differs among models (Table 3.17). Most of the difference, however, occurs among the Moderate and Low probability of occupancy categories. The

Table 3.17 Status of King Rail habitat under alternative models. The models differ in the amount of Potential Habitat that is ultimately predicted to have a Low, Moderate, or High probability of occupancy by breeding King Rail. However, if the focus is on High occupancy habitat for purposes of management action, the values are fairly consistent. All models predict that roughly 35-40% of the High occupancy habitat is held in GAP Status 1 and 2 lands, representing opportunities to form partnerships and immediately evaluate existing management actions or initiate new actions. All models also agree that roughly 50-60% of the High occupancy habitat is in GAP Status 4 lands without any known protection or management. This suggests there remains significant opportunity to expand the amount of habitat in permanent protection and management for King Rail.

		Probability of Occupancy (Hectares; % Ecoregion)			**GAP Conservation Status** (% of High Category)				**National Wildlife Refuge System** (% of High Category)
Model	**Error Rate** (Validation Data)	**High**	**Moderate**	**Low**	**1**	**2**	**3**	**4**	
Expert-Only BN	39.05 (2008 + 2009) 36.84 (2010)	41,685 (40)	45,214 (44)	16,086 (16)	13.8	22.4	10.7	53.2	21.8
Expert + 0809 Data BN	32.8 (2008 +2009) 31.58 (2010)	49,612 (48)	0 (0)	53,374 (52)	16.6	21.3	12.8	49.4	26.1
Expert + 2010 Data BN	30.48 (2008 +2009)	42,051 (41)	2,523 (2)	58,412 (57)	14.4	23.9	9.6	52.1	24.3
PRESENCE Data-Only	39.47 (2010)	33,487 (33)	53,775 (52)	15,723 (15)	16.6	20.8	5.4	57.2	27.4

proportion of the Ecoregion categorized as High probability of occupancy remains between 33-48% of the landscape. Roughly the same amount of this High category land remains within the refuge system (22-27%) or with no conservation protection (GAP status 4: 49-57%). Thus, in terms of acreage, these models do not present strongly conflicting views regarding either the current status of USFWS lands or the total protected acreage of King Rail habitat.

3.4 Discussion

To establish realistic population and habitat objectives, it is essential to know where King Rail occur in the landscape. If species occurrence data are too sparse to support inductive modeling approaches, then managers face three options: (1) convene experts to set objectives directly based on knowledge alone, (2) convene experts to construct a knowledge-based model upon which temporary objectives can be based, or (3) delay setting objectives until suitable empirical data can be collected. By constructing models that incorporated a range of expert knowledge and empirical data, our case study provided an opportunity to compare the relative outcomes of these strategies. We learned that models constructed from expert-knowledge alone can be very inaccurate. However, we also demonstrated that in highly variable systems, such as we observed with King Rail, data-driven models based on short-term studies or small sample sizes can be equally inaccurate. The combination of expert-knowledge and empirical data provided the most accurate predictions of King Rail occupancy within the Ecoregion for the time period of this study.

3.4.1 Sampling Design to Support Learning Objectives and Management Decisions

Network models can guide experimental design in support of adaptive monitoring. In adaptive monitoring programs, the sampling design evolves iteratively over time as new information emerges and as the research questions change (Lindenmayer and Likens 2009). In an adaptive management setting, multiple variables can potentially influence population dynamics or species–habitat associations. Resources allocated to monitoring in support of adaptive management are often inadequate to permit sampling across all levels of all variables every year. Adaptive monitoring can allocate the available resources most efficiently to support learning by the model and subsequent adaptive management. Network software includes tools to analyze model sensitivity to initial assumptions and uncertainty (Marcot et al. 2006), and this information facilitates designing a monitoring strategy that will maximize opportunities to refine the model and the hypotheses upon which it is based.

The BN models updated easily with addition of new data, but the sampling strategy has a potentially strong impact on how the models evolve. The design of a sampling strategy should be driven by the proposed application of the model. Data collected with a bias towards occupied habitat improved the accuracy and precision of positive predictions (i.e., decreased the frequency of false positives), but provided little learning benefit regarding negative predictions. If the model would primarily support decisions where false positives posed a higher risk than false negatives (e.g., acquisition of land based on modeled species presence), then such biased sampling could have benefits. However, if the model would support decisions where both false negatives and false positives posed high management risk, then a more balanced sampling strategy would be beneficial.

3.4.2 Importance of Assessing the Spatial Data

The accuracy of spatial models is limited by the accuracy of the spatial data from which they are constructed. If it has not been previously done, basic ground-truthing of spatial data should be part of early learning strategies. We identified and corrected land cover classification errors in the northern part of the Ecoregion. This area had been mapped as Salt Marsh, a land cover class which experts expected to have low probability of occupancy, when in fact it was Fresh/Oligohaline Marsh as experts had expected King Rail to favor. Had the map error not been noted and corrected, the frequent detections of King Rail in this area would have led the model to gradually update towards the false conclusion that Salt Marsh was consistently occupied by King Rail. Error in the map would inflate error in the Expert-Only model validation, resulting in the false conclusion that experts were incorrect about the habitat value of Salt Marsh. Furthermore, data collected to update the model would be associated with the incorrect land cover class, resulting in false learning.

Testing landscape variables that have been designed to serve as proxy for microhabitat variables is also critical. Therefore, if a model incorporates proxy data, early monitoring studies should allocate effort toward collecting associated microhabitat data. Experts may correctly identify relationships between microhabitat conditions and species distribution patterns, but these can be difficult to translate to landscape scale patterns. In this project, experts expected vegetation heterogeneity (species richness) to strongly influence King Rail habitat selection. As vegetation heterogeneity cannot be measured remotely, we designed a proxy variable (*NDVI*) based on the heterogeneity of reflectance values in remotely-sensed imagery. When this proxy variable was found non-competitive within the various PRESENCE models, we were able to explore whether this was due to expert error (richness does not correlate with King Rail occupancy) or failure of the proxy variable to capture the experts' observations (richness does not correlate with heterogeneity of NDVI values). Error in expert knowledge would require us to restructure the model, removing the uninformative node, but error in the proxy relationship would require us to consider other approaches to handling the spatial data to better represent this relationship.

3.4.3 Discretized Data in Bayesian Networks

BN models require all data to be represented as categorical variables to facilitate the complex calculations. Great care needs to be taken when defining and assessing the categories. Guidelines recommend that during model design, effort is made to define the minimum number of categories possible, as this minimizes the effort required to complete the conditional probability tables. We did not find any guidance for discretizing the response variable. However, we noted during model validation that the number of categories defined for the response variable strongly influence metrics of model accuracy; the greater the number of categories (e.g., the higher the precision of the prediction), the higher the overall percentage error, even though the predicted and observed data values do not change. The effect of discretizing the response variable is strongly seen in the difference in accuracy reported for results reported as two categories (Occupied versus Unoccupied) *versus* three (High, Moderate, Low Probability of Occupancy). Thus the modeler has great control over perceptions of the model's success. For models that would predict spatially-explicit results, we recommend mapping the continuous values (e.g., expected value of response), rather than the categorical values. Alternatively, we recommend managers *a priori* select the category thresholds based on the management decisions that a model will support. For example, if only sites with greater than 70% probability of occupancy would be considered for acquisition, then this would be the threshold distinguishing sites suitable from those unsuitable for acquisition.

3.5 Conclusions

Conservation and wildlife management decisions are always informed, to varying degrees, by expert knowledge (Perera et al. 2011). Only recently, however, have significant effort and advances been made to make this component of the decision process transparent and quantitative in support of landscape-scale adaptive management (Krueger et al. 2012; Perera et al. 2011; Nyberg et al. 2006). Despite concerns raised regarding the reliability of expert-knowledge, many expert-based models are created and applied to management decisions without rigorous validation. Our example shows that this could lead to ineffective application of management efforts; the Expert-Only model performed poorly. However, this is an acceptable and expected result over the short-term within an adaptive management setting where both success and failure lead to learning. Our example illustrates that such error can be corrected when empirical data are collected and applied to update the models.

The poor performance of the Data-Only models (both BN and PRESENCE versions) provides further support for formally eliciting and integrating expert knowledge into the foundation of species and habitat management plans. King Rail are a secretive species requiring long-term data collection (>10 years) to observe population trends (Conway et al. 2008b). This observation, coupled with our own experience of the highly variable environmental conditions between seasons, suggests that establishing precise and accurate species-habitat association would also require long-term data collection. By taking advantage of the >100 cumulative years of expert experience and observation, the BN models not only provided testable hypotheses, but also guided surveys to selectively target sources of highest uncertainty or greatest potential impact, thereby maximizing the opportunity to adaptively improve the model. As a result, the Expert+Data models updated with data from the BN guided sampling design provided the greatest accuracy overall.

Chapter 4

POPULATION AND HABITAT ESTIMATES BASED ON SPATIALLY-EXPLICIT PROBABILITY OF OCCUPANCY PREDICTIONS

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4.1 Introduction

Not all populations are suited to traditional population estimation techniques by capture-recapture or distance sampling. This is true of King Rail which exhibit secretive behaviors and have low capture rates. Distance sampling is not appropriate in call-back surveys, as birds may adjust their location in response to the calls played (Buckland et al. 2001). However, it is possible to extend occupancy modeling and estimate mean abundance from repeated survey detection/non-detection data (Royle and Nichols 2003). The relationships between detection, occupancy, and abundance have been the focus of intense and ongoing research (e.g., Royle et al. 2005; He and Gaston 2003; Royle and Nichols 2003). Basic occupancy models assume that heterogeneity in detection probability among spatial units is a function of abundance; higher abundance corresponds to higher probability of detection (Royle and Nichols 2003). When evidence of species presence is detected in plots or transects, the resulting data provide an index of relative abundance.

Indices of relative abundance can be used to calculate population estimates, but strong assumptions must be met. For example, to estimate population size based on species count data from North American Breeding Bird Survey transects, the North American Landbird Conservation Plan (Rich et al. 2004) applied three major assumptions (Thogmartin 2010; Thogmartin et al. 2006). In the absence of direct empirical evidence, these assumptions defined the detection-area relationship (a species-specific standard radius distance within which individuals available for detection would be detected), the call-pair relationship (the number of birds represented by one detection), and time-of-day availability relationship (6^{th}-order polynomial model fit to daily temporal variation in species detection). Sensitivity analysis illustrated that the final population estimates are highly sensitive to small variation in the parameter values set under each assumption (detection area, birds per detection, and temporal effects on detection) used to translate relative to absolute measures of abundance (Thogmartin 2010; Thogmartin et al. 2006).

Our Bayesian network (BN) models predict the probability of King Rails occupying a given site during the breeding season. After integrating the 2008 and 2009 empirical data (see Chapter 3), the updated BN predicts a landscape where 90,178 ha of the mapped marsh habitat ranges in value from 0.17 to 0.75 probability of occupancy (Figures 3.5B – 3.8B). These occupancy maps provide insight into the potential risks and benefits of management actions at alternative locations. However, before deciding where to act, the USFWS and their partners typically set conservation and habitat objectives defined in terms of desired acreage of habitat or abundance of a given species. Therefore, the next step to develop the BN models for conservation planning application is to translate the occupancy estimates into habitat and population estimates that can serve as a baseline. Accomplishing this task requires several critical decisions to define thresholds in the face of ecological uncertainty and management risk. The first set of decisions defines the assumptions that will relate occupancy estimates to population estimates at the scale of a survey site. The second set of decisions defines the assumptions that will allow the mapped occupancy estimates to be aggregated into habitat and population estimates at the Ecoregional scale.

4.2 Methods

4.2.1 Effective Survey Area and Individuals per Call Response

As conducted in the Breeding Bird Survey data in the Landbird Plan (Rich et al. 2004), we began by setting assumptions regarding detection area and birds per detection for our call-back survey data. We did not need to make assumptions about temporal effects because the repeated survey method (three surveys per site per season) provided empirical data to directly estimate temporal variation in detection. For example, we found and accounted for differences between years and among survey periods in 2008 when we calculated the probability of occupancy in relation to landscape characteristics (Chapter 3). While we could not do formal distance sampling to calculate survey plot abundance, the field crew had estimated distance to each King Rail detected. Effective survey area is the area in which a bird would be detected if it were to call or move within the observers' field of view (Johnson et al. 2009). Using data from our own field crews and data from one of our experts who had conducted surveys in the Ecoregion, we calculated a fixed effective survey area. Regarding birds per detection, we also used the standard assumption that detection of one individual during the breeding season (e.g., a call-back response) is indicative of the presence of a breeding pair. However, we also followed the advice of Thogmartin (2010) and present the sensitivity of population estimates to this assumption.

4.2.2 Point Count Abundance and Density

We used the Royle/Nichols Abundance Induced Heterogeneity Model in PRESENCE (Royle and Nichols 2003) to estimate the mean site abundance of King Rail (null model). We specifically estimated abundance for points scored by the BN model to be Low or High probability of occupancy (there were too few Moderate probability sites to complete the calculations). We calculated the mean abundance (1) across all points, (2) for points predicted by the BNs to have Low probability of occupancy (probability <0.5), and (3) for points predicted to have High probability of occupancy (probability $\geq$ 0.5). Data met Poisson distribution assumption (Chi-square = 4.33, P = 0.11). We used the effective survey area and assumption of one pair per call-back response in the conversion of observed abundance values to density values.

4.2.2.1 From Raster Grid Cell Occupancy Predictions to Ecoregional Habitat and Abundance Estimates

The BNs predict the probability of occupancy at the scale of 30-m raster grid cells by considering the landscape characteristics and context of each grid cell individually. Call-back surveys measure occupancy and relative abundance at the scale of the effective survey distance. However, breeding King Rail occupy territories that exceed the size of both grid cells and the effective survey distance. Marsh patch sizes in the Ecoregional landscape include patches as small as a single grid cell, much too small to support a breeding pair. Also, there are some very large patches composed primarily of Low occupancy habitat (probability of occupancy < 0.33). The simplest method to calculate Ecoregional abundance would be to simply multiply all Potential Habitat by the density estimate calculated from the Royle/Nichols mean abundance across all surveys (which included Low, Moderate, and High probability of occupancy points). However, the increased precision of

BN occupancy predictions allowed us to take into account the variability in habitat quality when estimating habitat area and population size.

4.2.2.2 Habitat Area Estimates

To transcribe predictions of probability of occupancy to an estimate of habitat area occupied required that we (1) define an occupancy threshold to distinguish occupied from unoccupied habitat, and (2) define a breeding territory size to ensure abundance calculations are not applied to patches too small to support a breeding pair.

We focused the occupancy threshold on management rather than biological thresholds. By definition, all Potential Habitat is potentially occupied at some point in time regardless of size or location. However, not all Potential Habitat is equally likely to be occupied nor is all Potential Habitat equally suited to specific management actions. For example, the statistical probability of occupancy threshold of 0.5 may not be the most appropriate threshold to distinguish occupied from unoccupied habitat in all cases. Instead, the appropriate occupancy threshold could depend on the management application and the management agency's risk tolerance. With the BN models, managers could define what probability is high enough to warrant conservation action (or low enough to warrant inaction) and then apply this threshold to the occupancy maps to see how much habitat, in which locations, are suited to the specific action. In the absence of a specific example management application, we demonstrate the sensitivity of the habitat area estimate for thresholds defined at 0.1 increments from 0.2 to 0.7 probability of occupancy.

In contrast, the territory size threshold is primarily a biological threshold. King Rails require a certain amount of territory to successfully reproduce. However, the size of the territory needed is uncertain and probably variable depending on the quality of habitat included. Given this uncertainty, the setting of a threshold to include or exclude patches from an estimate of habitat should also be informed by management priorities and risk tolerance. If too small a size is selected, many small fragments will be included and the amount of habitat may be over-estimated. If too large a size is selected, the population could be under-estimated as many small occupied patches are excluded. To illustrate sensitivity of habitat estimates to the territory size threshold, we calculated the total habitat area for a variety of threshold values (2-ha increments from 0 to 30 ha). This range of values was based on our own research results and review of recent literature. Both thresholds serve to restrict the area of marsh that is incorporated into estimates of available habitat. The result is more conservative habitat and population estimates than simpler aspatial estimates that multiply total acreage by average density. In addition, by restricting which grid cells count towards the total habitat, the number of locations identified as available for potential management action are reduced.

4.2.2.3 Population Abundance Estimates

We calculated population estimates by two methods. The first method simply multiplied the calculated mean density from our Royle/Nichols analysis by the total area of Potential Habitat. We again used a range of territory size thresholds to exclude patches smaller than a King Rail breeding territory. We did not need to include an occupancy threshold, because the Royle/Nichols analysis incorporated sites across the full range of probability of occupancy values in the BN models. However, the second method took advantage of the BN probability of occupancy values. We had sampled enough sites predicted by the BN to be either Low (probability < 0.5) or High (probability ≥ 0.5) occupancy that we were able to obtain an independent Royle/Nichols density estimate for each category. Therefore, after first eliminating patches smaller than a King Rail breeding territory, we applied matching density estimates to the total area of Low and High occupancy habitat.

4.3 Results

4.3.1 Effective Survey Area

To define the radius distance for the effective survey area, we reviewed the distance estimates in secretive marsh bird survey data from studies in the Ecoregion (Table 4.1). At Back Bay National Wildlife Refuge a professional ornithologist (B. Ake: Table 4.1) conducted marsh bird call-back surveys for six years (USFWS, unpublished data). Of King Rail detections that noted distance estimates, 100% were heard within 200 m of the observer. Our less experienced field crews similarly documented 98% of King Rail detections within 200 m, with minimal difference between observers. We concluded that 12.5 ha (200-m radius) was the effective survey area for King Rail in our region; the ability to detect at least one King Rail, if available for detection, would approach one at this distance.

Table 4.1. King Rail detection distances. Unpublished data from Back Bay National Wildlife Refuge (B. Ake) and data from our surveys across the Ecoregion. Observer 1 and 2 were randomly assigned at each survey.

King Rail Detections						
Observer:	B. Ake (2000 – 2006)		Observer 1 (2009)		Observer 2(2009)	
Distance (m)	#	%	#	%	#	%
0-50	10	14	27	54	28	54
51-100	44	62	16	32	16	31
101-150	14	20	2	4	2	4
151-200	3	4	3	6	4	8
>200	0	0	2	4	2	4

4.3.2 Point Count Abundance and Density

Two models were competitive in the Royle/Nichols analysis. The top model calculated abundance per sampled unit in relation to two covariates: Low versus High probability of occupancy ($AICw$ = 0.72). The top model had an r greater than 0.15, and therefore could yield reliable estimates. The alternative model with three covariates (Low, Moderate, and High probability of occupancy) was also competitive ($\Delta AIC = 2$, $AICw$=0.37), but no information was gained as the Moderate and Low categories received the same estimates. Therefore, we selected the top model for all following analyses. This model estimated an abundance per sampled survey area of 0.98 ± 0.29 breeding pairs in High and 0.50 ± 0.17 breeding pairs in Low probability of occupancy habitat. This abundance estimate translated to a density of 12.8 ha per breeding pair in High and 25.3 ha per breeding pair in Low probability of occupancy habitat.

4.3.3 Estimated Area of King Rail Breeding Habitat

The total area of potential habitat was 90,178 ha. After excluding sites identified as (1) likely unoccupied and (2) too small to support a breeding pair, the estimated total area of King Rail breeding habitat ranged from 1,725 ha to just under 90,000 ha (Figure 4.1). The estimate was much more sensitive to the occupancy threshold than the territory size threshold. At the traditional threshold of 0.5 to distinguish occupied versus unoccupied habitat, the estimate of breeding habitat ranged from 43,641 ha (with a 15-ha minimum patch size threshold) to 47,435 ha (with no minimum patch size threshold). The sensitivity of the habitat area estimate to the occupancy and territory size threshold translates to uncertainty when estimating the amount of land currently in conservation or land available for conservation (Table 4.2). For example, when the threshold selected to define occupied habitat for the purposes of setting management objectives is shifted from 0.5 to 0.7, the amount of marsh habitat identified as non-habitat more than doubles (Table 4.2). If the occupancy threshold is 0.5, but the territory size threshold is decreased from 16 ha to 4 ha, the estimated area of habitat in conservation increases 4% from 7,777 ha to 8,055 ha. At a 0.7 occupancy threshold, the increase is 188% from 17 ha to 49 ha (Table 4.2).

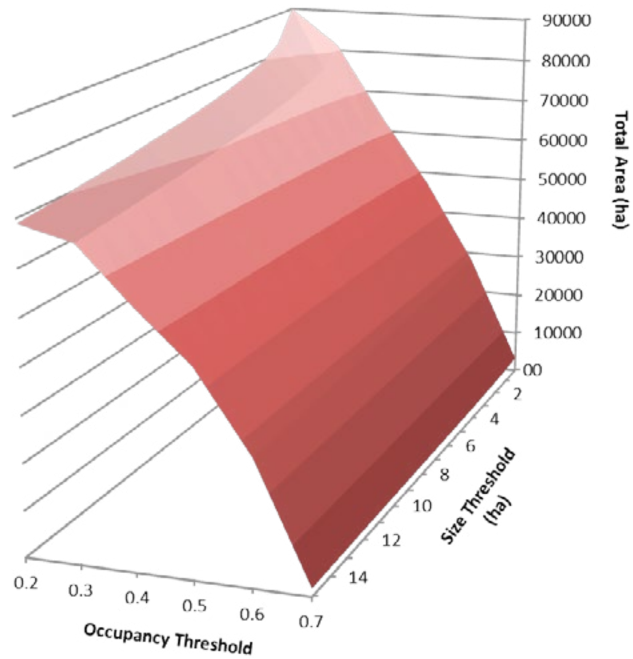

Figure 4.1 Sensitivity analysis for occupancy and territory size thresholds. Response is total area of habitat occupied by breeding King Rail. Habitat estimates are much more sensitive to occupancy than territory size thresholds. Most small Potential Habitat patches are predicted to have low occupancy, so the effect of the territory size threshold is only evident when low occupancy sites are included in the habitat estimate.

<u>4.3.4 Estimated Size of King Rail Breeding Population</u>

The proportion of Low to High probability of occupancy habitat is unequal in the Ecoregion. Therefore, the two methods of calculating population size produced different results (Table 4.3). If habitat quality is ignored (e.g., the Royle/Nichols mean density estimate is applied to all habitat greater than the territory size threshold) the population size estimate is 4,665 ± SE 1,292 breeding pairs. If, however, Low and High probability of occupancy are evaluated separately, the total estimated Ecoregional population size is 5,390 ± SE 1,826 breeding pairs.

When we restricted the population calculation to only consider patches larger than the mean area per detection (13 ha in High and 25 ha in Low probability of occupancy habitat) the population estimates dropped dramatically, to 3,899 ± SE 1,321 breeding pairs. Most of this loss is due to exclusion of many small Low probability patches. The population estimate for Low probability habitat dropped by 72%, while the estimate for High probability patches only dropped by 7%.

4.4 Discussion

<u>4.4.1 Advances in King Rail Knowledge and Data</u>

The same data collected to validate the BN models enabled us to run Royle/Nichols models to estimate population abundance within sample units and habitat area per individual. The density values that we measured corresponded well to other King Rail results (Table 4.4). Working in a

Table 4.2. Habitat conservation status for King Rail. The sensitivity of habitat estimates to occupancy and territory size thresholds has implications for how conservation status is assessed. The table shows the total habitat area and habitat area by GAP Conservation Status for Unoccupied and Occupied Potential Habitat. The occupancy threshold, the expected probability of occupancy by King Rail, is set to 0.7 in the left table and 0.5 in the right table. The total area of Unoccupied Potential Habitat under each scenario is highlighted (red boxes). Area estimates for Occupied Potential Habitat are further assessed by patch size, with area sums provided for two thresholds: 4 ha (blue text) and 16 ha (red text). The total area of GAP Potential Habitat is shown at the bottom (black text).

	GAP Conservation Status				Total Area
Size (ha)	1	2	3	4	(ha)
Unoccupied Habitat Marsh Habitat with F(KIRA) < 0.7					
all sizes	10849	15973	9829	50301	86952
Occupied Habitat: Marsh Habitat with E(KIRA) ≥ 0.7					
0.09 - 2 ha	61	102	109	324	596
2 - 4 ha	10	99	48	117	274
4 - 6 ha	13	30	25	50	117
6 - 8 ha	7	42	7	48	104
8 - 10 ha		18	37	53	107
10 - 12 ha		22	6	60	88
12 - 14 ha	13	50		65	128
14 - 16 ha		43		59	102
16 - 18 ha		16			16
18 - 20 ha				19	19
20 - 22 ha		42		41	84
22 - 24 ha		14		8	22
24 - 26 ha				25	25
26 - 28 ha				27	27
28 - 30 ha				115	115
> 30 ha	17	433	111	840	1401
Area > 4 ha	**49**	**710**	**186**	**1412**	**2356**
Area > 16 ha	**17**	**505**	**111**	**1076**	**1709**
Total Area (ha)	**10969**	**16884**	**10171**	**52154**	**90178**

	GAP Conservation Status				Total Area
Size (ha)	1	2	3	4	(ha)
Unoccupied Habitat: Marsh Habitat with F(KIRA) < 0.5					
all sizes	2749	6853	3954	29187	42744
Occupied Habitat: Marsh Habitat with E(KIRA) ≥ 0.5					
0.09 - 2 ha	105	245	67	720	1137
2 - 4 ha	59	131	13	409	612
4 - 6 ha	61	124	15	329	528
6 - 8 ha	61	122	67	251	501
8 - 10 ha	42	90	17	194	344
10 - 12 ha	9	74	10	171	264
12 - 14 ha		116	4	114	234
14 - 16 ha	105	44		194	343
16 - 18 ha	24	97	6	229	356
18 - 20 ha		56		152	208
20 - 22 ha	22	62	63	85	231
22 - 24 ha	91	80	22	240	434
24 - 26 ha	20		0	181	201
26 - 28 ha	27			27	54
28 - 30 ha	21	94	29	88	232
> 30 ha	7571	8696	5904	19585	41755
Area > 4 ha	**8055**	**9654**	**6138**	**21838**	**45685**
Area > 16 ha	**7777**	**9084**	**6024**	**20586**	**43471**
Total Area (ha)	**10969**	**16884**	**10171**	**52154**	**90178**

Table 4.3 Estimates of Breeding King Rail abundance. Sample units are the 200 m radius (12.6 ha) call-back survey plots. Average abundance per plot was converted to hectares per bird and extrapolated to the whole Ecoregional landscape. We first calculated an Ecoregional total estimate based on all empirical data (All Sample Units, blue text). We then employed a second method, taking advantage of the greater precision of the BN models. This method divided the empirical data into sites predicted to be High or Low probability of occupancy sites and calculated abundance values specific to these sets. We summed the totals from both sets to obtain an Ecoregional total (red text). The total is presented both before (unrestricted) and after (restricted by patch size) we removed patches smaller than the estimated hectares per bird.

			95% Confidence Intervals	
	Estimate	SE	Lower	Upper
ALL SAMPLE UNITS				
Detection probability (*r*)	0.25	0.07	0.12	0.39
Average Abundance per Sample Unit (λ)	0.65	0.18	0.29	1.01
Hectares per Bird	19.33	5.35	8.84	29.83
Population Size	**4665**	**1292**	**2133**	**7197**
HIGH PROBABLITY OF OCCUPANCY SAMPLE UNITS ONLY				
Detection probability (*r*)	0.28	0.08	0.15	0.46
Average Abundance per Sample Unit (λ)	0.98	0.29	0.42	1.55
Hectares per Bird	12.81	3.76	5.44	20.18
Population Size (Unrestricted Patch Size)	3703	1087	1572	5834
Population Size (Patches ≥ 13 ha)	3430	1007	1456	5404
LOW PROBABLITY OF OCCUPANCY SAMPLE UNITS ONLY				
Detection probability (*r*)	0.17	0.05	0.08	0.30
Average Abundance per Sample Unit (λ)	0.50	0.17	0.17	0.83
Hectares per Bird	25.34	8.58	8.52	42.15
Population Size (Unrestricted Patch Size)	1687	571	567	2807
Population Size (Patches ≥ 25 ha)	469	159	158	781
Total High + Low (Unrestricted)	5390	1826	1812	8968
Total High + Low (Restricted by Patch Size)	3899	1321	1311	6487

1 Sample Unit = 12.6 hectares
Total hectares = 90178
High hectares = 42744
Low hectares = 47434

Table 4.4. Comparison of King Rail density and territory size estimates. Several recent and ongoing studies provide the first estimates of the density and territory size of breeding King Rail.

Citation	Location	Method	Estimate
Rogers et al. (In Press)	NC and VA: natural and impounded oligohaline coastal marshes	Royle/Nichols Abundance Induced Heterogeneity Model	1 King Rail per: • 8.33 ha at Mackay Island NWR • 16.67 ha at Back Bay NWR
Pickens (2012)	LA and TX: natural and controlled, fresh and oligohaline coastal marshes	Telemetry use kernels	95% use territory size: • 4.38 ± 0.58 ha McFaddin NWR • 11.85 ± 4.12 ha Cameron Prairie • 27.31 ± 5.51 ha JD Murphree WMA
Pierluissi 2006; Pierluissi & King 2008	MO and IL: commercial rice fields	Nest search of fields (nests/km^2)	1 nest per: • 29.4 ha (3.4 ± 0.87 nests/km^2) 2004 • 20.8 ha (4.8 ± 0.93 nests/km^2) 2005
This study	NC and VA: natural and impounded, fresh/oligohaline and brackish coastal marshes	Royle/Nichols Abundance Induced Heterogeneity Model	1 King Rail per: 12.8 ha in High P(Occupancy) 25.3 ha in Low P(Occupancy)

subarea of the Ecoregion in 2010, in High probability of occupancy habitat, Rogers et al. (2013) calculated area per King Rail as 8.33 ha to 16.67 ha. These values concur with our estimate of 12.81 ± SE 3.76 ha for the same High occupancy habitat. Working in coastal marsh habitats of Louisiana and Texas, Pickens (2012) used telemetry to calculate King Rail home range kernel density estimates and movement characteristics. Their marshes were unmanaged and managed fresh and oligohaline marshes. They observed King Rail to maintain highly distinct territories with little overlap (B. Pickens, 2012). Mean home range size with a 95% kernel varied from 4.38 ± 0.58 ha (oligohaline marsh on a refuge) to 27.31 ± 5.51 ha (oligohaline marsh in a managed drawdown area). Their results provide the first direct estimates of King Rail breeding territory size, though it remains uncertain how habitat needs may differ in highly dynamic systems such as the wind-tide systems of the Ecoregion. At the time this project initiated, no estimate of King Rail territory size was available. Experts had no knowledge of habitat area requirements and, therefore, the patch size thresholds selected to discretize the BN models (Small < 81 ha ; Medium = 81 to 202 ha; Large > 202 ha) were somewhat arbitrary. Given the data resulting from our own and related work, the discrete categories could now be redefined to better reflect the new knowledge.

Ordinarily, the Royle-Nichols density estimates cannot be extrapolated beyond the sample units. However, given that our sample units had been selected to represent the range of habitat conditions within the Ecoregion, we extrapolated to generate ecoregional population estimates. *These estimates should be treated with extreme caution.* Our purposes here were to demonstrate the sensitivity of population estimates to basic assumptions and to demonstrate the advantage of linking density predictions to spatially-explicit categorical predictions of occupancy. For the first time, managers have an estimate of the relative amount of habitat needed in Low versus High probability of occupancy habitat to protect a single King Rail pair.

4.4.2 Tracking and Testing Assumptions

Habitat and population estimates are sensitive to assumptions regarding detection rates, area requirements of breeding pairs, and other thresholds selected to distinguish habitat from non-habitat. It is critical that these assumptions be clearly stated, understood by resource managers, held constant throughout a study or monitoring program, and regularly evaluated. Evaluations are especially valuable to identify instances when small changes in model values can change perceptions of whether agencies are succeeding or failing at conservation objectives. We illustrated sensitivity for some assumptions (e.g., probability of occupancy and territory size thresholds), but depending on the management decision to be supported, other assumptions could be more critical (e.g., detection rate, effective survey area). Thus, again, the BN model serves as a template upon which to explore management scenarios and questions of risks versus benefits of alternative actions given certain assumptions.

4.4.3 Spatial versus Aspatial Estimates

The national and regional habitat and population estimates for King Rail were generated aspatially, ignoring heterogeneity in breeding habitat quality and habitat patch size. Breeding territories are rarely of homogenous habitat quality and, for some species, there exists a tradeoff between territory size and the quality of habitat within the territory. Our models provide a distinct advantage by predicting a broad range of breeding habitat quality, represented as a range in the probability of occupancy. Furthermore, spatial analysis allows exclusion of patches that are likely too small to support breeding pairs, with the ability to set different minimum patch sizes based on habitat quality.

4.5 Conclusions

Our BN models alone do not predict total habitat area or populations size. The total area of habitat remains the same as that predicted as potential habitat by GAP models, but this habitat is now depicted based on a threshold applied to a continuous probability of occupancy. Managers must interact with model, either *a priori* or *a posteriori*, to define occupancy thresholds to select a suitable threshold to distinguish occupied habitat from unoccupied habitat. While even low occupancy habitat may have biological relevance, the same habitat could have low management relevance, depending on the management action under consideration. When combined with an effective sampling design (to calculate Royle-Nichols abundance), the spatially-explicit occupancy predictions of the BN models support estimation of habitat area and population size. The model structure facilitated sensitivity analyses based on occupancy and patch size thresholds. These same sensitivity analyses point toward the importance of continued biological research; high sensitivity of population estimates to patch size thresholds indicate that this knowledge gap impedes effective planning.

Chapter 5

CONCLUSIONS AND MANAGEMENT IMPLICATIONS

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5.1 Introduction

There is growing emphasis on the need for conservation practices to be strategic. The National Ecological Assessment Team defined Strategic Habitat Conservation (Figure 5.1) as: "a structured, science-driven approach for making efficient, transparent decisions about where and how to expend Service resources for species, or groups of species, that are limited by the amount or quality of habitat." (NEAT 2006) They further specify that strategic conservation is guided by an adaptive management framework which uses monitoring and evaluation as tools to improve design and delivery of conservation plans.

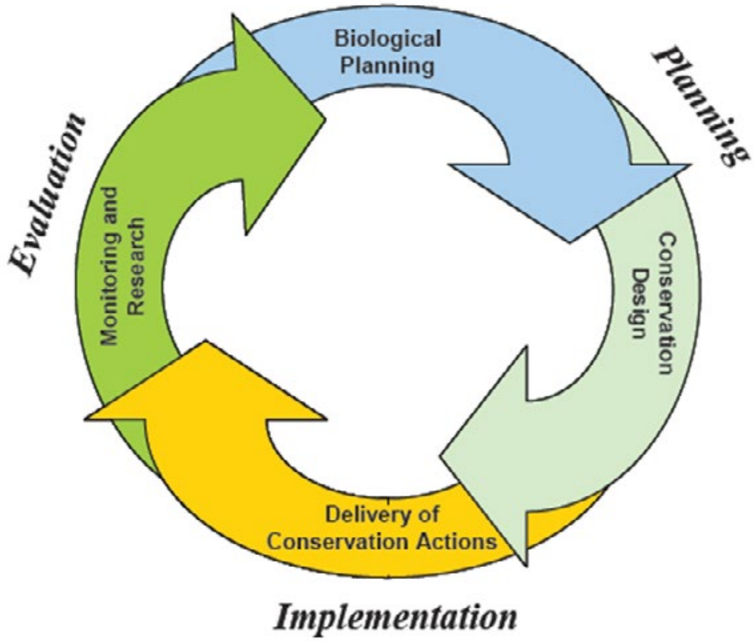

Figure 5.1. Adaptive management cycle. USFWS Strategic Habitat Conservation vision of adaptive management cycle (Fig. 1 from NEAT 2006)

Through study of King Rail in the eastern North Carolina and southeastern Virginia landscape (Ecoregion), we explored applications of Bayesian networks (BNs) to the Strategic Habitat Conservation approach. We used the BNs to:

1. summarize Ecoregional expert knowledge and data,
2. translate and visually represent expert judgments as testable, mechanistic ecological hypotheses,
3. generate testable, spatially-explicit predictions of the probability of occupancy,
4. design a field sampling strategy based on expert and model uncertainty,
5. test the accuracy of expert knowledge,
6. integrate new data into the knowledge framework, and
7. support estimates of habitat area and population size.

Based on this list, the BN models offer significant value to the Strategic Habitat Conservation approach as a framework for organizing, visualizing, and updating the data that inform management decisions.

5.2 Project Outcomes

5.2.1 Progress toward King Rail Strategic Habitat Conservation

Data from Breeding Bird Survey (BBS) and anecdotal evidence suggest that King Rail have been experiencing range-wide decline and range contraction (Cooper 2008; Hunter et al. 2006). The Southeast Waterbird Conservation Plan (SEWCP, Hunter et al. 2006) estimated a Southeast Coastal

Plain population of 830 pairs and recommended an increase to 6,000 pairs. However, as noted in the King Rail Conservation Action Plan (KRCAP, Cooper 2008), regional BBS data are too sparse to set precise population objectives based on historical targets or to define landscape scale species-habitat relationships to clearly prioritize habitat for conservation. The action plan stated that an alternative approach to setting objectives for such secretive species may be to establish a target in terms of frequency of detection (Cooper 2008). We took a similar approach by developing models that elicit and then spatially predict a related metric: the probability of occupancy by breeding King Rail. Assumptions inherent to occupancy modeling then allowed us to estimate the area of breeding habitat and the abundance of breeding King Rails. Field validation of the models not only tested and improved model accuracy, but also tested expert hypotheses about King Rail species-habitat relationships and landscape-microhabitat data relationships.

5.2.1.1 Probability of Occupancy Model and Maps

The BN models predict occupancy on a continuous scale and report confidence as a standard deviation of the expected value (Chapter 2). The maps included in this report (Chapter 2) illustrate how the greater precision of these estimates allow differentiation among areas previously designated simply as potential habitat and comparison of occupancy expectation among refuges (or other local land management units). With these continuous data, land managers could define breeding habitat based on project specific thresholds for occupancy and confidence (Chapter 4). In some cases, depending on a land manager's risk aversion, acquiring a parcel of land offering a high certainty of Moderate probability of occupancy might be preferred to acquiring a parcel with a low certainty of High probability of occupancy. In this manner, the new maps support a more nuanced assessment of existing population and habitat distribution into decision risk analysis. Learning to use these data effectively will require some training and adjustment, but will allow for more strategic decisions than simply protecting more potential habitat at any location.

We were able to explore the relative and incremental value of landscape versus site data for predicting King Rail occupancy in the Ecoregion by comparing competing models in PRESENCE (Chapter 3). Experts had expressed limited confidence that King Rail occupancy patterns were driven by landscape characteristics, generally favoring microhabitat characteristics when ranking variables (Chapter 2). This is not surprising, given that landscape scale patterns such as patch size or connectivity are not as easily perceived as microhabitat conditions by biologists working in the marshes. However, based on our results, landscape data provide a slightly better predictive value for occupancy than microhabitat data; PRESENCE models with landscape data generally outperformed models with microhabitat data (Chapter 3). Patch size and connectivity, factors assumed to positively impact dispersal among patches, were the most informative landscape variables (Chapter 3). The presence of woody shrub species, the only significant microhabitat variable, reduced the probability of King Rail occupancy (Chapter 3) as observed in other studies (e.g., Darrah and Krementz 2009; Pierluissi and King 2006).

5.2.1.2 Ecoregional Population and Habitat Estimates

To achieve population objectives set forth in the SEWCP, it was recommended a preliminary increase of emergent wetlands by 100,000 acres (40,469 ha) east of the Mississippi Alluvial Valley, with the restoration of 10,000 acres (4,047 ha) specifically recommended for North Carolina (Hunter et al.

2006). To effectively contribute towards this goal, the Ecoregion must have an accurate estimate of available breeding habitat, the quality of the habitat, and the restoration potential of the habitat. Within the Ecoregion, the Southeast Gap Analysis Program models identified 75,500 ha of marsh habitat as potential habitat for breeding King Rail (McKerrow et al. 2006). Our models refined this classification, but also demonstrated that a single value answer is elusive, and likely inappropriate, due to dependence on both biological assumptions and management objectives (Chapter 4).

We demonstrated that population and habitat estimates are sensitive to assumptions regarding detection rates and territory size, as well as the probability threshold selected to distinguish occupied from unoccupied habitat (Chapter 4). Using an occupancy threshold of 0.5 probability and a territory size threshold of 4 ha, we calculated a total of 45,700 ha of habitat. Of this habitat, approximately 8,000 ha were situated in lands under full protection and management (Gap Status 1 lands), while almost 22,000 ha had no documented protection or management activities (Gap Status 4 lands). Our population estimates ranged from approximately 3,900 to 5,400 birds, depending upon the method used to generate the estimate. This is significantly more than the 830 pairs estimated for the entire Southeast Coastal Plain. Therefore, based on our model results, we would agree with the authors of the Southeast Waterbird Conservation Plan (Hunter et al. 2006) that the previous estimates based on BBS data likely underestimate the true number of breeding King Rail in the Ecoregion. Moreover, the overall detection and occupancy rates in this study area were much higher than in most King Rail studies, indicating that the Ecoregion may be an important area to focus conservation efforts.

5.2.1.3 Local Decision Support to Achieve Ecoregional, Regional, and National Objectives

Our BN, as constructed, is a descriptive model that informs decisions rather than a tool that indicates an optimal decision. To identify the "best" decision, a land manager must still weigh the relative costs, risks, and benefits of a decision to decide how much uncertainty a specific decision he or she can support. However, our BNs support such value-based decision processes precisely because they estimate the probability of occupancy along a continuous scale and provide the associated precision of the estimate. These data apply to decisions at multiple scales. Refuges within the Ecoregion can be compared to identify those most likely to contribute towards King Rail population and habitat objectives. Land parcels within a refuges' acquisition boundary can be easily compared for their potential to contribute towards goals to increase the number of acres and King Rail under permanent protection in managed habitat. Within refuges, high occupancy, high confidence sites could be identified as locations for King Rail education programs and habitat demonstration areas. Where habitat with a high probability of King Rail occupancy occurs outside refuges, the USFWS could pursue opportunities to collaborate with partner agencies or private land owners to protect and manage these lands for breeding King Rail. Management actions that might negatively impact breeding King Rail could also be considered in light of the probability of occupancy. For example, the level of confidence associated with predictions on the probability of occupancy at a given site could be used to determine when decisions about management actions unfavorable to King Rail require additional input, such as field surveys prior to approval.

5.2.2 Bayesian Networks Support Strategic Habitat Conservation

5.2.2.1 Value as an Archival and Communication Tool

Effective archival and communication tools will be critical to successfully implement Strategic Habitat Conservation of species and habitat. An objective of SHC Element 1, Biological Planning, is to gather all available knowledge and data, often through workshops and literature review. As this information is gathered, it must be translated from a raw collection of assorted opinions, judgments, and observations into a formalized model of population-habitat relationships with measureable goals and objectives. The BN model provides a method to organize this information into both a conceptual model and a conditional probability model. Furthermore, adaptive management is a long-term objective, often longer than any one biologist's or manager's local tenure. By formally encoding existing knowledge, BNs provide a tool to archive and transfer accumulated knowledge from one biologist or land manager to the next.

5.2.2.2 Value as a Spatially Predictive Tool

As learning proceeded, the BN occupancy predictions became more accurate (Chapter 4). Though the gains were small, they were evident consistently across all methods and all data resources used to update and test the models. Given two years' empirical data, both Expert-Only and Data-Only BN models performed poorly (i.e., lower percent accuracy) relative to models that had conditional probabilities based on a combination of expert knowledge and empirical data (Chapter 4). Prediction error differed between the expert and data models, with experts generally over-predicting and data under-predicting the probability of occupancy (Chapter 4). With short-term monitoring data, the Expert+Data BN models also outperformed the best PRESENCE data-based models.

5.2.2.3 Value as a Hypothesis Testing and Learning Tool

We conducted two years of empirical data collection to explore methods to validate and update the BN models. The models improved in both accuracy and precision as new data were incorporated, although a longer time series would be important to smooth out effects of extreme events (e.g., very dry or very wet years, such as we observed). Conway et al. (2008) recommended at least ten years' data collection to achieve suitable power to measure population trends in secretive species such as King Rail. We propose that similar time frames may be necessary to obtain a clear, consistent picture of King Rail landscape and microhabitat associations. Our concern is not just the detectability of the species, but also the high temporal variability of the coastal marsh systems which they inhabit. Thus, while our two years' data were adequate to explore the utility and limitations of BN models, they were not adequate to make strong conclusions about King Rail habitat associations, as evidenced by the high standard error observed for even the top model parameters within PRESENCE (Chapter 3)

Our field program targeted three areas of potential error and uncertainty: expert hypotheses, proxy relationships between microhabitat and landscape variables, and the accuracy of underlying spatial data (land cover classification). We found evidence of error in all three areas with management implications. Expert hypotheses could be wrong, as seen most clearly in the mismatch between experts' ranking of model variables and the data-driven ranking of these same variables within the PRESENCE model sets (Chapter 3). In such cases, the Variance Reduction scores are observed to change as new data are added and managers would then have the option to drop variables that have no impact on predicted occupancy. Although some proxy relationships worked well across scales (e.g., mapped marsh salinity classification and empirically measured site salinity values), others did not (e.g., heterogeneity of the mapped Normalized Difference Vegetation Index scores and empirically measured site vegetation richness) (Chapter 3). In the case where a proxy variable predicts well for the associated microhabitat condition, but does not improve the predictive value of the model, a decision could be made to remove the uninformative variable. Although overall we found the Southeast Gap Analysis Program data to be accurate, we did find errors (e.g., marsh habitat classification based on salinity) that would have profoundly affected estimates of available habitat and potential measures of success (e.g., the percentage of King Rail habitat in conservation) if uncorrected. Ground-truthing the spatial data that underlie species and habitat models and management plans is as important as ground-truthing the model and plan predictions. Without information from both tests, it is difficult to conclude what proportion of prediction error results from data error versus model assumptions.

A second King Rail study in the Ecoregion provided an independent data set to analyze BN learning strategies. While our sampling strategy had been designed to sample a diverse range of landscape conditions representing the full scale of predicted probability of occupancy, the Rogers (2011) study targeted sites with high predicted probability of occurrence. Independent validation (or learning) datasets are often borrowed from studies that were not designed as validation studies. By comparing outcomes of learning and testing with a designed versus biased sample, we found that both could support effective learning (Chapter 3). However, caution must be exercised when interpreting and applying results from a biased sample. Data collected solely from sites predicted to be occupied only test for true and false positives. No information is gained regarding true negatives or false negatives. While some learning about negative predictions will occur based on the false positive observations, no learning can occur regarding rates of false negatives. Accurate prediction of unoccupied sites may not be important in all management contexts, but the impact of uneven sampling designs should be carefully considered in light of management objectives and the proposed application of the BN models.

5.2.2.4 Value as a Conservation Decision Support Tool

Decisions which the USFWS hopes to support with tools such as our BN model include the prioritization of sites for management within refuges, the estimation of population and habitat contributions of existing conservation lands, and the identification of opportunities for collaboration or land acquisition. While our model provides the biological and geographic data necessary to inform such decisions, our model does not directly indicate which single decision from a set of alternatives would be optimal. The final decision would also require data about acceptable risks (e.g., what level of uncertainty is acceptable), costs, and expected benefits. The BN modeling approach can integrate these social and agency values to assess the expected outcome and stakeholder satisfaction through addition of decision and utility nodes (e.g., Irwin and Mickett Kennedy 2008; Marcot et al. 2001). Additional elicitation would be required to allow managers and stakeholders to define their expected level of satisfaction (i.e., utility) for each alternative outcome. We did not proceed with this aspect of the modeling because (1) we would not have the opportunity to conduct the management experiments necessary to test this component of a BN, and (2) the general methods to elicit, test, and update decision and utility nodes are similar to those demonstrated here for the biological component of the model (for an excellent guide to decision analysis incorporating BN models, see Conroy and Peterson 2013).

5.3 Lessons Learned and Recommendations

5.3.1 Expert Knowledge, Rigorously Elicited and Encoded, is a Valuable Resource

Through this project we learned much about expert knowledge elicitation (Drew and Collazo 2012; Drew and Perera 2011). Expert knowledge has always played a role in natural resource management and conservation, however, its role has been largely informal and ad hoc. Significant recent efforts have focused on establishing knowledge elicitation methods that are rigorous and transparent (Krueger et al. 2012; Perera et al. 2011). Our BN model was primarily biological, defining King Rail habitat associations and estimating occupancy. In management applications, we recommend that such biological models be more closely linked into an actual decision framework (e.g., Structured Decision Making, Conroy and Peterson 2013). As we have shown, many of the data processing choices and model assumptions have implications for decision risk and cost analysis, so these should be informed by management priorities and objectives. To this end, we recommend elicitation tools such as the Open Standards for the Practice of Conservation (Conservation Measures Partnership 2007; Salafsky et al. 2002) and Structured Decision Making (Conroy and Peterson 2013; Martin et al. 2009; Clemen and Reilly 2001). These tools provide a formal language and framework for elicitation of expert knowledge, as well as management goals, expectations, and measures of success. These broad, qualitative elicitations are well suited to gather all participants (spatial data modelers, species and habitat experts, managers) at an initial design workshop. Later, through surveys or personal interviews, specialist knowledge from individual experts can be elicited using quantitative tools, such as Elicitator (Low Choy et al. 2011) to encode knowledge as statistical probabilities.

In the past, it has been common to seek consensus in expert elicitation. However, we found that differences among experts offered insights into potentially important geographic variation (e.g., expert knowledge comes from refuges that differ strongly in available habitat features) or temporal trends (e.g., experts knowledge comes from different seasons or historical periods) (Drew and Collazo 2012). While consensus is necessary to define a single project scope and objective, we recommend that the knowledge and judgements of each expert be elicited and maintained as an individual record. Group elicitation methods in workshop settings may still be used, but effort should be made to note experts' initial judgments prior to group discussion.

- *Allocate Adequate Time to Prepare and Test Expert Elicitations*

  Preparation includes (1) literature review to establish familiarity with specialized terminology and disciplinary perspectives, (2) spatial data collection and assessment to determine which data resources and which scales best characterize regional landscape patterns, and (3) elicitation design and testing. Based on our experience on this and other projects, a month per model node (i.e., per explanatory variable) is probably a minimum estimate of the time required.

• *Characterize Experts' Domain of Expertise*
A domain of expertise is the geographic and temporal dimensions of an expert's experience. It is critical to know how the domain of knowledge compares among experts and between the experts and the project extent (Drew and Collazo 2012). Knowledge of an expert's domain makes it easier to distinguish elicitation responses based on direct experience from those based on plausible extrapolation. It also allows more critical examination of differences among experts to determine when these differences reflect different interpretations of similar experiences *versus* different experiences (Drew and Collazo 2012).

• *Separate Qualitative and Quantitative Elicitations*
Based on experience in this project, we now propose projects begin with a workshop that gathers modelers, managers, and experts to review available data and expected management alternatives. This review allows definition of a clear scope and project objectives statements that narrows down which modeling strategies to employ, which information to elicit, and which assumptions to test with sensitivity analyses. Through the remainder of the project, most quantitative information can be elicited from individuals or small groups. This creates more work for the elicitator, but can reduce expert fatigue and drop-out rates. Additional workshops or webinar review sessions can be held as necessary to review model structure and output.

5.3.2 Critical Role of Spatial Data Quality and Interpretation

Species and habitat distribution models inform many, if not most, fish and wildlife management decisions. Yet, the data upon which these models rest vary greatly in quality. Any uncertainty or error in the underlying spatial data layers will pass to the distribution models and any subsequent population or habitat area estimates and projections. We corrected one major error in the Southeast Gap Analysis Program data when we corrected the land cover classification of marshes surrounding Back Bay (from Salt Marsh to Fresh-Oligohaline Marsh). Another error, the absence of mapped marsh habitat at Mattamuskeet NWR, could not easily be corrected. This error is noteworthy, in that it leads to exclusion of an area known to support King Rail, possibly at higher than average abundance (Cooper 2008). The King Rail breeding habitat of the Mattamuskeet NWR simply does not map well at a 30-m resolution classified from leaf-off aerial imagery and when man-made freshwater impoundments are flooded for migrating and wintering waterfowl. However, ecologists knowledgeable of King Rail and managers knowledgeable of Ecoregional marshes, if oriented to the spatial data and allowed to review data layers, often can identify potential errors for either correction or to highlight areas needing special attention during model review.

The accurate spatial representation of our expert hypotheses was dependent upon the accuracy of the spatial data and proxy relationships, yet these components of accuracy are often overlooked in model validation or updating. We believe that learning and validation of the underlying data and proxy relationships should be part of the adaptive management process. If these linkages and dependencies are ignored, there exists the possibility that expert hypotheses will be assumed false, when in fact the error lies in the scale or calculation used to express the hypothesis within the constraints of existing spatial data.

If the model being developed is to provide spatially-explicit output, then it is critical that the model developers, experts, and end-users (i.e., managers) communicate frequently throughout the process. Characteristics of spatial data (e.g., resolution, extent, accuracy, precision, date, etc.) establish limits to what can and cannot be measured or modeled remotely to inform management objectives. Such limits should inform discussions of project scope, vision, and objectives at a project's initiation and then again throughout the discussion of possible threats, drivers, and other ecological relationships to be represented in the BN. This does not mean that experts and managers must become proficient at GIS technology, but rather they must be able to envision the implications of their familiar habitats being represented, for example, in discrete 30-m grid cells grouped according to an eight neighbor rule. Once the model is ready for validation and updating, sampling design should be informed by the limitations of the data as much as by limitations in knowledge of species ecology. For example, the close communication among participants during model development might indicate the spatial data quality or proxy data relationships represent greater potential sources of model uncertainty than the actual species-habitat relationships, and thus should receive higher priority for sampling and learning.

- *Allocate Adequate Resources for Spatial Data Assessment, Preparation and Analysis*
  Spatial data resources include not just the necessary hardware and software to run analyses of large raster images, but also the human resources to do this work. The preparation of spatial data required exploration and summary of landscape patterns at multiple scales. Modeling at Ecoregional extent at fine enough resolution to observe variation within refuges required frequent transfer of large datasets from the mapping to the modeling software and back again. The task of processing the spatial data, including the frequent transfer of data between ArcGIS, PRESENCE, and Netica, was the single largest time expenditure in this project (≥75% of project time).

- *Involve Experts and Managers in Explorations of Spatial Data*
  Spatial data are sensitive to many processing decisions, yet very often alternative processing decisions relate to alternative ecological assumptions (Laurent et al. 2011). With adequate time allocated to planning, it should be possible to allow experts and managers to review spatial data and comment upon which decision alternatives best represent relevant ecological theory and the scale of their knowledge.

5.3.3 Perform Sensitivity Analyses

We have highlighted decisions made at each stage in the modeling and updating processes that impact model output. Variance in the output translates to variance in habitat and population estimates. Assumptions about occupancy rates, effective survey area, territory size and composition, and number of individuals per call response then can magnify variance in population and habitat estimates. Sensitivity analysis characterizes which assumptions have the greatest impact on population and habitat estimates.

5.3.4 Monitoring and Model Updating Require Rigorous Data Management

Diagnostic tools available to explore BN models, such as variance reduction metrics, provide insight useful for developing adaptive monitoring strategies (Chapter 1). Ideally, plans for monitoring should be developed in parallel with the BN model development and data should be collected to improve the BN model generally or to test specific management hypotheses. This ensures that the expert-knowledge elicitation and the model output reference the same units and methods as the empirical data collection methods.

• *Predict an Outcome that is Unambiguous*
Our model predicted breeding season occupancy as measured by a specific survey method and statistical analysis. The numeric predictions were thus directly testable. The entire elicitation and model construction process maintained a very clear focus on this method as the standard means to quantify occupancy (N.B. but see discussion below on occupancy theory)

• *Allow Adequate Time to Fully Validate Models*
In highly variable systems, one to two years data collection will be inadequate to fully validate a model (and certainly inadequate to construct a data-driven model). This will be especially true when a BN is designed to predict a long-term average and range, yet the empirical data capture a limited snap-shot perspective of the same phenomena.

• *Test both Expert Error and Data Error*
Until proven otherwise, model validation should proceed assuming that the spatial data and the expert knowledge could be wrong. Error in either would lead to false understanding of King Rail habitat associations and inaccurate population and habitat estimates. However, continued collection of empirical data and model updating can only correct expert error., unless specific effort is made to test the spatial data Error in the spatial data will limit the potential accuracy of the models.

• *Provide Resources to Design a Data Management Plan*
Planning for data management should also begin at the start, rather than the end, of the project. If annual monitoring data are to be incorporated for learning, then consideration should be given to how these data will be received and processed. The BN learning methods are quite simple, but translating the data from GIS to Netica, and back again, is challenging. The development of an automated process would facilitate application of the BNs within an adaptive management setting. Furthermore, the maps produced are best viewed as dynamic rather than static products. Predicted values and their precision will change as learning progress. Even more important though, to support management decisions that differ in risk tolerance, these maps would be best linked to a tool that allows managers to interactively set occupancy probability and

confidence thresholds prior to evaluating the status of various sites in relation to specific management questions.

5.3.5 Understand Occupancy Theory and Abundance Estimates

Traditionally, when the USFWS defined quantitative population estimates or objectives, they have done so in terms of abundance of individuals or breeding pairs. The focus on occupancy rates, specifically detection-adjusted occupancy rates, is still relatively novel. Relationships between expert knowledge of species-habitat associations, PRESENCE calculated detection and occupancy rates, and the spatially-explicit representation of probability of occupancy require further investigation. Several issues arose during the course of this project which would benefit from further research.

The first issue relates to using expert knowledge to populate conditional probability tables in a model predicting occupancy. During elicitation, it became unclear whether we should elicit detection (e.g., where had the expert observed the species) or occupancy (e.g., where did the expert believe the species to be, regardless of whether they had directly detected it). Experts do make claims outside their own direct detection experience, such as when they state that King Rail likely occupy interior marsh habitat despite never themselves having observed King Rail in interior marsh habitat. A common elicitation technique to obtain probability estimates is to substitute frequency for probability (Low-Choy et al. 2011); experts are asked how many surveys in a given type of habitat would yield a King Rail detection. The frequency-probability substitution is generally an accepted practice in expert elicitation, however, this same question also substitutes detection for occupancy. Thus, the prior probability of occupancy in the initial Expert-Only BN best represents an occupancy estimate unadjusted for detection. In this case, we would expect the expert-based models to under-predict occupancy relative to the data-driven PRESENCE models which adjust for individuals present, but not detected. However, instead experts generally over-predict both detection and, therefore, occupancy. Our elicitation data did not allow us to distinguish between experts' knowledge of detection and occupancy, so we consider this an important area for further research to improve elicitation design and model robustness.

A second issue relates to the uncertain relationship between occupancy as predicted by the BN (and projected onto raster maps) and occupancy as measured by PRESENCE. PRESENCE models measure occupancy in a single season and assume closure to immigration to and emigration from a discrete sample unit during the season. The purpose of the BN is to provide a spatially-explicit representation of the long-term frequency of occupancy of a given site within a continuous landscape. In effect, the BN seeks to inform managers regarding which locations are rarely, and which frequently, occupied by breeding King Rail. With this knowledge, and the assumption that King Rail will generally occupy higher quality habitat prior to occupying lower quality habitat, managers can then act to conserve or manage the best available habitat to benefit the most King Rails. The BN models do not assume closure because marsh patches are often much larger than a breeding territory and, furthermore, the effective survey area for the call-back surveys is much smaller than a territory. It is unclear how these differences between the model assumptions impact the utility of PRESENCE models to validate and update the BN models. We expect that, over time, repeated measurement of the instantaneous occupancy should result in an estimate of the asymptotic occupancy predicted by the BN models. However, longer term research and simulation modeling should be performed to test the relationships between the BN and the PRESENCE occupancy estimates.

Several challenges likely increased model error. First, there were the challenges related to detection of secretive species and the assumption of full occupancy of suitable habitat. Despite the fact that species are either present or absent in a given location, we found our experts to be cautious in their predictions. Experts rarely hypothesized a probability of occupancy above 0.7 or below 0.3; the only landscape condition that they predicted to never host King Rail was the salt marsh land cover class. Then, in our field sampling, we failed to detect King Rail in the majority of habitat, including sites that presented similar landscape characteristics to sites where detections had occured. Our naïve occupancy estimate was well below that suggested by any expert. This fundamental difference between observed and predicted values resulted in very high error rates. However, as we show in Chapter 4, these are errors that can reduce quickly through adaptive sampling and model updating.

- *Define Occupancy Terminology then Elicit both Occupancy and Detection*
  The relationship between detection and occupancy probabilities must be clear to experts prior to elicitation to ensure clear communication of the respective probabilities. Questions should be included that highlight experts' beliefs about the relationship between these two rates in their domain of expertise. Given that validation data would be analyzed in PRESENCE, which allows parameterization of both detection and occupancy models, it is useful to ask experts to consider whether each variable they propose is acting on detection, occupancy, or both.

- *Consider Occupancy in Relation to Management Questions*
  Although a probability of occupancy of 0.5 is the common default threshold for distinguishing occupied from unoccupied habitat, there could be cases when a more (or less) conservative threshold would be appropriate.

5.4 Conclusions

Continental, national, and even regional conservation planning documents now exist for many taxa, but few offer clearly defined, quantitative population and habitat objectives. Instead, large scale plans (e.g., King Rail Conservation Action Plan, Cooper 2008; Southeast United States Regional Waterbird Conservation Plan, Hunter et al. 2006; North American Waterbird Conservation Plan, Kushlan et al. 2002, 2006 supplement) primarily identify priority species and habitats, characterize dominant threats, guide research towards critical knowledge gaps, and offer guidance for regional allocation or management and research effort. The availability of biological and geospatial data, as well as historical population estimates, is often a limiting factor in agencies' ability to set quantitative population and habitat objectives.

At the initiation of the project, King Rail was not only a data-poor species but also an expert-poor species. Knowledge of the species' breeding distribution and ecology in the Ecoregion was limited to personal observations, anecdotal accounts, and unpublished survey data. Published studies from other regions, whose results shaped our experts' knowledge and our elicitation strategies, provided little insight to landscape-scale patterns and processes. The most generous habitat area estimates available came from the SEGAP data, which distinguished potential habitat from non-habitat. The SEGAP data indicated that some areas, such as Mackay Island National Wildlife Refuge, had a high proportion of potential habitat, but these models provided neither an estimate of habitat quality nor an estimate of the confidence of the prediction. These data could support the development of coarse, large-scale estimates (e.g., national and regional), but could not provide the resolution necessary to support habitat management or acquisition decisions (e.g local scale action). Our project generated the data necessary to set quantitative, refuge-scale objectives – but did not define specific objectives. BNs can be used to set objectives, but these require additional elicitation of value and risk judgments from stakeholders and managers.

Generating and maintaining a BN occupancy model is not a rapid process, but the result is a solid foundation for adaptive management. The USFWS policy of Strategic Habitat Conservation (NEAT 2006) mandates that the agency's conservation actions (1) be coordinated across regional landscapes, (2) be founded on the best available science (with testable assumptions), and (3) support adaptive management through monitoring and assessment of action outcomes. The BNs met criteria of sound science because, although based on expert knowledge, they are transparent and subject to peer review, readily challenged or corrected as new evidence emerges, and clearly state underlying assumptions and uncertainties (Tear et al . 2005). The theoretical foundation of these models could be improved by further research regarding the linkages between the instantaneous occupancy measured annually via PRESENCE and the asymptotic occupancy represented in the BN models. Lastly, the methodological ease of constructing and maintaining the models could be improved through better integration of standardized elicitation techniques (e.g., Open Standards, Elicitator) and data management tools.

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