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SHALLOW LAKES IN MINNESOTA: CAN WE PREDICT THE GOOD, THE BAD, AND THE VULNERABLE?

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SUMMARY OF FINDINGS

Our initial efforts focused on (1) using linear mixed-effects models to predict total phosphorus (TP) levels in shallow MN lakes from watershed and in-lake features and (2) developing an integrated framework to classify lake states (clear or turbid) and estimate state-dependent relationships between key system variables in shallow lakes. Our best TP model to date includes relative abundance of benthivorous fish, average lake depth, and proportion of forest and shrublands within lake watersheds. Higher TP levels were observed in lakes with high benthivore mass, relatively shallow depth, and low proportions of forest and shrublands in adjacent watersheds. Chlorophyll *a* (Chla) concentration, TP, and relative abundance of submerged aquatic vegetation (SAV) were incorporated into a Bayesian latent variable regression framework to classify lake states and identify relationships between nutrients and turbidity. The model produced reasonable classifications and regression relationships, though modifications to incorporate nutrient thresholds and improve coefficient estimates are ongoing. These two analyses will eventually allow us to use Chla, SAV, and TP to assess the relative state transition risk of shallow lakes in MN to aid in management decisions.

INTRODUCTION

Shallow lake ecology

Shallow lakes generally conform to one of two alternative stable states: a clear state with primary production dominated by submerged aquatic vegetation (SAV) and a turbid state with phytoplankton dominating over SAV. Excessive nutrient inputs from current and historical land use, food web-mediated influences and sediment disturbance caused by planktivorous and benthivorous fish, and wind all drive transitions to, and impact the resilience of, turbid states. Shallow lakes with high nutrient levels are especially prone to explosive phytoplankton “blooms” when phosphorus (P) is readily available. Submerged aquatic vegetation, which sustains the diverse invertebrate communities that provide important food sources for waterfowl, is reduced in this turbid, algae-dominated state. Parasites associated with amphibian malformations likely have higher prevalence in turbid lakes (Johnson and Chase 2004), and nitrogen may accumulate at higher rates (Zimmer et al. 2003). It is not surprising that key goals for shallow lake management are to prevent shifts from clear to turbid states, to induce shifts from turbid to clear states, and to maintain the natural resilience of clear-water shallow lakes.

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Alternative states have been described from field studies of shallow lakes in the US (Hanson and Butler 1994, Hansel-Welch et al. 2003, Zimmer et al. 2009), Great Britain (Moss et al. 1996), the Netherlands (Gulati and Van Donk 2002, Scheffer 2004), Denmark (Søndergaard et al. 2007), Sweden (Hargeby et al. 1994), New Zealand (Mitchell et al. 1988), and China (Wang et al. 2014). Complex ecological and physical mechanisms are responsible for maintaining the stability of each alternative state, such as competition between primary producers. When SAV declines, phytoplankton abundance typically increases, limiting light reaching the lake bottom and further restricting SAV in a positive-feedback fashion. Additionally, when SAV is sparse, sediments are easily disturbed by benthivorous fish and waves. Suspended sediments further increase turbidity, and mobilized P stimulates even higher phytoplankton growth rates. In contrast, in clear-state lakes, SAV remains widely distributed and helps maintain water clarity by stabilizing sediments and taking up nutrients. Charophytes (*Chara* spp.) often accompany clear-water conditions in Minnesota lakes and are believed to release algal toxins (Berger and Schageri 2004) and provide refuge for zooplankton, which may further reduce the phytoplankton population and help stabilize clear-water conditions.

Theory of regime shifts

Shallow lakes are notoriously difficult to restore after shifting from clear to turbid states, with turbid conditions frequently returning within 5-10 years following lake management (Søndergaard et al. 2007). Theoretical models are useful for understanding why reducing nutrient input to previous levels does not always induce the reverse state shift. For example, Figure 1 shows a bifurcation diagram derived from a model describing shallow lake dynamics similar to those in Scheffer and Carpenter (2003) and Scheffer (2004). At low nutrient levels (left of “flip down!” threshold in Figure 1), lakes can only exist in the clear stable state. At high nutrient levels (right of the “flip up!” threshold in Figure 1), lakes only exist in the turbid state. In between these two thresholds, the system exhibits hysteresis in which two different steady states are possible under the same nutrient conditions, depending on whether the initial turbidity levels lie above or below the unstable state in this region of bistability (dotted line in Figure 1).

The bifurcation diagram is also useful for understanding temporal dynamics and shifts between stable states. If a lake is in the clear state with high SAV (lower solid line) and nutrient input increases beyond the “flip up” bifurcation point, the lake will likely transition quickly to the turbid state with low SAV (upper solid line). Once SAV is lost, the internal loading of nutrients becomes hard to control, and nutrient input must be substantially reduced to the lower “flip down” bifurcation point to reverse the state shift (Scheffer and Carpenter 2003). In practice, such a drastic nutrient reduction may not be possible. Alternatively, managers may attempt to induce a state shift by forcing the system across the unstable point, e.g., by decreasing the planktivore and benthivore populations with rotenone (if nutrients can at least be reduced to the region of bistability). These transitions may be short-lived, however, since perturbations to the system (e.g., fish colonization) can force the lake back to the turbid state.

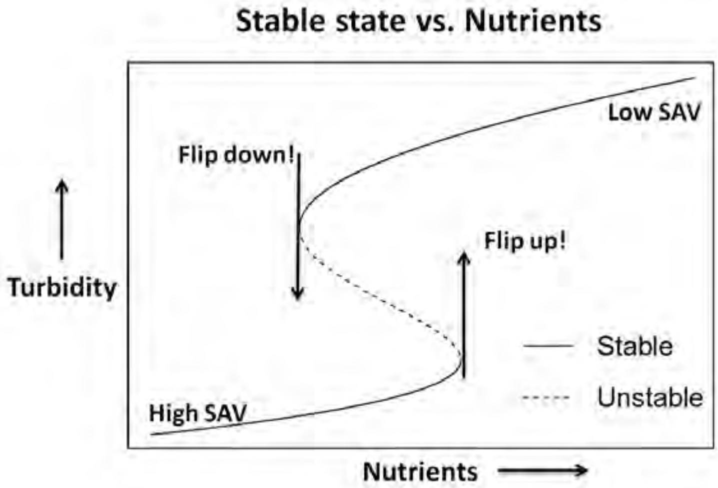

Figure 1. Bifurcation diagram from a theoretical model for state shifts in shallow lakes.

Earlier research provides strong evidence that shallow lakes in Minnesota generally conform to conceptual models like those summarized by Scheffer and Carpenter (2003) and in Figure 1 here. One notable example is Lake Christina, a large shallow lake near Fergus Falls, Minnesota. To improve habitat quality for migrating waterfowl, the lake has been rehabilitated (using fish toxicants) three times during the past five decades. In each case, improved water quality and clear-state characteristics followed lake management, but the lake persistently transitioned back to turbid conditions during 5-10 years after treatment (Hanson and Butler 1994, Hansel-Welch et al. 2003, Hobbs et al. 2012). Zimmer et al. (2009) surveyed 75 shallow Minnesota lakes and showed that a large proportion of these sites had characteristics of turbid-water conditions. More recently, our research team monitored eight rehabilitated shallow lakes, and data indicated that stable clear-state conditions had not become established in these sites during 2-4 years following management (Hanson et al. unpublished data).

These studies illustrate the fact that managers need better tools to evaluate relative transition risks of shallow lakes in Minnesota. Theoretical models suggest that to prevent undesirable state shifts in shallow lakes, we need to more accurately predict implications of nutrient levels, land use practices, lake depth, geographic location, and biological community features to identify the current attracting states and to assess the likelihood that lakes will flip to turbid states. A better understanding of transition risks will also help lake managers identify lakes that are good candidates for rehabilitation and will inform future conservation strategies for both lakes and adjacent watershed areas.

OBJECTIVES

The overarching objectives of this study are stated below. However, the Methods and Discussion sections here concern only the first two objectives because approaches for Objectives 3 and 4 have not been formalized and may depend upon results of analyses supporting Objectives 1 and 2.

1. Model Total Phosphorus (TP) in shallow Minnesota lakes using depth, benthivore mass, upstream watershed land cover variables, and geographic location of lakes.

2. Develop a modeling framework that allows us to classify lake states and estimate state-dependent relationships between measures of turbidity (Chla) and nutrients (TP) (similar to Figure 1).
3. Extend the model in Objective 2 to allow for temporal dynamics, with state transitions modeled as a function of varying nutrient levels and biological variables (e.g., zooplankton size, fish community types and densities).
4. Using results from Objectives 1-3, develop a tool to compare the relative risk of state transitions for different lakes. Conceptually, this objective can be viewed as attempting to determine where lakes “sit” in Figure 1, and for lakes falling within the region of bistability, the likelihood of the lake transitioning as the result of (possibly management-induced) perturbations (e.g., fish colonization or extirpation).

In summary, Objective 1 will help place lakes along the *x*-axis of Figure 1. Objective 2 will attempt to capture the salient features of Figure 1 using statistical models that can be applied to data from lakes in MN. Objective 3 will determine how far lakes may shift both horizontally and vertically in Figure 1 as a result of various perturbations. Lastly, Objective 4 aims to translate, as necessary, the results of more complex mathematical and statistical models into a simpler quantitative tool that can be used by wildlife managers to make informed decisions regarding shallow lakes and their management potential.

METHODS

Data

Analyses described here are based on data from two sources. First, we compiled a “research lakes dataset” (hearafter, research lakes), based on a sampling of 132 lakes surveyed by our research team once in July during each of three consecutive years, 2009-2011. Measures of TP, Total Nitrogen, turbidity (nephelometric turbidity units or NTUs), depth, chlorophyll *a* concentration (hereafter, Chla), as well as relative abundances of SAV, fish (planktivores, benthivores, piscivores), and invertebrates (cladocera and copepods) were obtained in each year (details of data gathering and project logistics are summarized in Hanson 2012). Land cover data in the upstream watershed of each research lake were derived by summarizing manually-delineated cover type polygons that were created using on-screen digitizing procedures in ArcGIS. Color air photos from 2008 were used as the primary interpretive reference for distinguishing cover types, with 2001 National Land Cover Database and 1991 GAP land-cover used to corroborate air photo interpretations as needed. A second similar set of water quality and land cover data was developed from 330 additional lakes using data provided by the MNDNR Shallow Lakes Program (hereafter program lakes). Preliminary modeling has focused on data from research lakes, but program lake data will also be incorporated into the analyses.

TP Model

We fit a series of linear mixed effects models, using the ‘nlme’ package in R (Pinheiro and Bates 2006), to describe within- and between-lake variability in the natural logarithm of TP. We included a random intercept for each lake to account for correlation among repeated measurements. The fixed explanatory variables we considered were depth, total benthivore abundance/presence, common carp abundance/presence, bullhead abundance/presence, watershed area to lake area ratio, proportion of different upstream watershed land cover types, and ECS Province. We also considered aggregate land cover variables, such as Total Agriculture (row crops, pasture, other ag), Disturbance (Total Ag, residential, roads, other impervious surfaces) and Filters (woodlands, shrubs), in addition to specific land cover types. We determined the most parsimonious model by comparing AIC values of candidate models, and model assumptions were checked with residual and Q-Q plots. Twelve lakes in the Red Lake Region were removed due to difficulties in distinguishing unique watershed boundaries. Additionally, we investigated the effects of removing two lakes with an average depth of five meters or greater on model choice and parameter estimates.

State classification and estimation of Chla/TP relationships

Following Zimmer et al. (2009), we used TP as a surrogate for P input (*x*-axis) and Chla as a metric for turbidity (*y*-axis) to create a diagram similar to Figure 1. In contrast to Zimmer et al. (2009), however, we used a Bayesian latent variable regression framework to both classify discrete steady states (clear/turbid) and to estimate state-dependent relationships between TP and Chla together in one model. In this framework, we treated the state of each lake (clear or turbid) as a latent variable, used logistic regression to model the probability of being in the turbid state as a function of SAV mass and TP, and estimated state-dependent relationships between TP and Chla using linear regression after taking the natural logarithm of both variables. We chose informative priors to ensure that the probability of being turbid decreased with SAV mass, increased with TP, and that the slopes describing the relationships between Chla and TP were positive.

We ran separate models in JAGS (Plummer 2003) for each of the three years, and examined convergence using trace plots and the Gelman-Rubin convergence statistic (Gelman and Rubin 1992). We classified a lake as turbid (clear) if over half of the sampled states from the MCMC chains were turbid (clear) for that lake. We estimated regression coefficients using means of the posterior distributions.

PRELIMINARY RESULTS

TP Model

The most parsimonious of the candidate models, as determined by AIC, included three continuous explanatory variables: percent filters (woodlands/shrubs) in the upstream watershed, log(benthivore kg +1), and depth (see Table 1 for parameter estimates and standard errors). TP decreased as the percentage of woodlands and shrubs in the upstream watershed increased, as depth increased, and as the relative mass of benthivores decreased (Table 1, Figure 2). Percent filters had the lowest AIC of all single predictor models, and total benthivore mass was a better predictor than benthivore presence, bullhead mass/presence, and carp mass/presence. ECS Province was not a significant predictor of TP after the inclusion of percent filters, and the ratio of watershed area to lake area was not significant after the inclusion of percent filters, benthivores, or depth. Replacing depth with the natural logarithm of depth resulted in a model with a similar AIC as the best-fit model (see Table 1 for coefficient estimates). We also observed a significant positive interaction between percent filters and depth (but not for the logarithm of depth). Finally, the removal of two very deep lakes did not affect model choice or estimation (Table 1).

The joint impacts of benthivores and woodlands on TP are better seen by considering lakes within a restricted range of depths. Figure 3 shows that for lakes with average depths between 2.0-2.3 meters, TP decreases as the percentage of filters in the watershed rises, and TP tends to increase with benthivore mass regardless of filter percentage. It is worth noting that while percent filters is a better predictor than ECS Province, provinces also differ by filter percentage, with the Prairie Parkland having the lowest percentage of filters in the lake watersheds and the Laurentian Mixed Forest having the greatest percentage of filters (Figures 3, 4).

State classification and estimation of Chla/TP relationships

We ran the Bayesian latent regression model separately for each year. The model produced reasonable state classifications and linear relationships between log(Chla) and log(TP) (results from 2009 are shown in Figure 5). Lakes classified as clear have higher SAV mass compared to lakes classified as turbid, and both the probability of being turbid and the expected Chla value in a lake increase with TP.

For year 2009, lake classifications match those produced using the methods described in Zimmer et al. (2009) for 92% of the lakes, and the linear regression slope estimates are also similar, though standard errors are larger for the Bayesian analysis (results not shown). Results for year 2010 are similar. However, classifications for year 2011 matched Zimmer et al. (2009) for only 55% of lakes, and coefficient estimates also differed. Further investigation revealed outliers and probable misclassifications of clear, deep lakes with low Chla, low TP, and low SAV mass by the Bayesian latent variable regression model.

Table 1. Regression coefficients for linear mixed effects model for log(TP). The first column of coefficient estimates and standard errors includes all lakes with depth measured in meters. The second column of estimates is the same model but with two lakes with an average depth of five or more meters removed. The third column of estimates includes all lakes but with depth measured in log(m).

Parameter	**Estimate (SE) (All lakes)**	**Estimate (SE) (Deep lakes removed)**	**Estimate (SE) (All lakes, log Depth)**
Intercept	4.74 (0.11)	4.74 (0.12)	4.53 (0.092)
Percent filters (Woods/Shrubs)	-1.41 (0.17)	-1.43 (0.17)	-1.39 (0.17)
log(benthivore kg + 1)	0.17 (0.035)	0.17 (.036)	0.18 (0.035)
Depth	-0.19 (0.057)	-0.18 (.064)	-0.33 (0.097)
Lake intercept SD	0.48	0.49	0.48
Within-lake residual SD	0.51	0.52	0.51

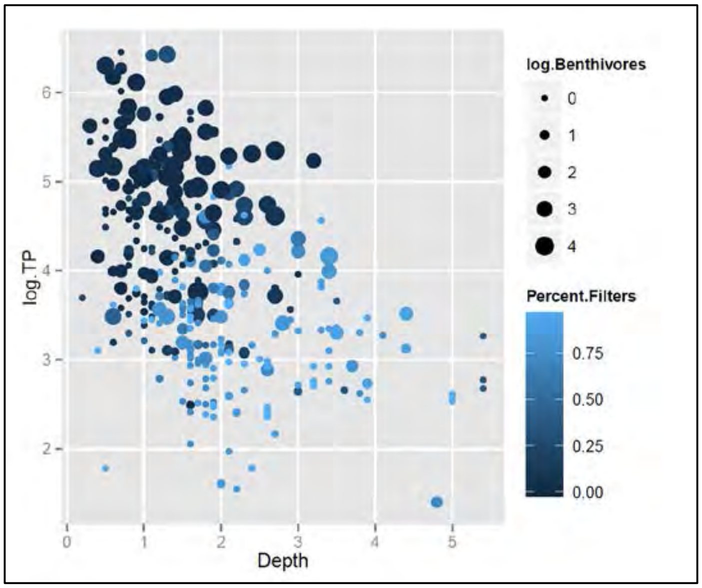

Figure 2. Log(TP) with three best predictors: percentage of filters (woodlands/shrubs) in the upstream watershed, log(benthivore kg +1), and depth.

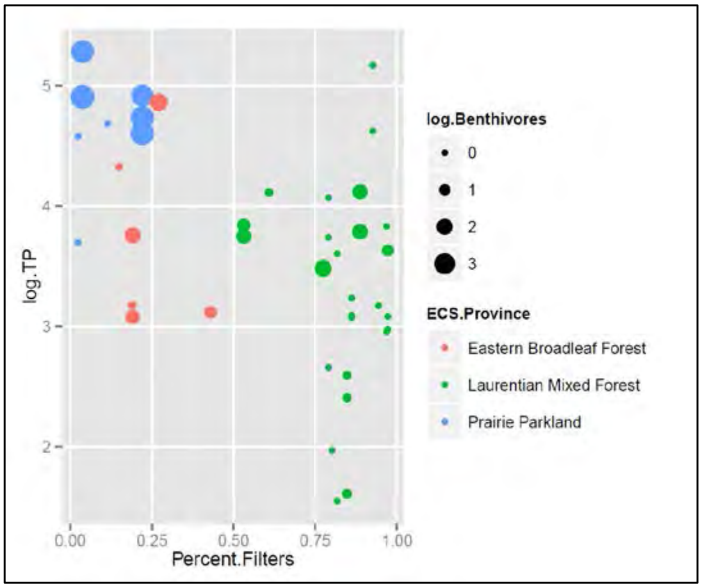

Figure 3. Log(TP) vs. percent filters for lakes with depth between 2.0-2.3 meters. Point size is proportional to log(benthivore mass +1), and color corresponds to the ECS Province of the lake.

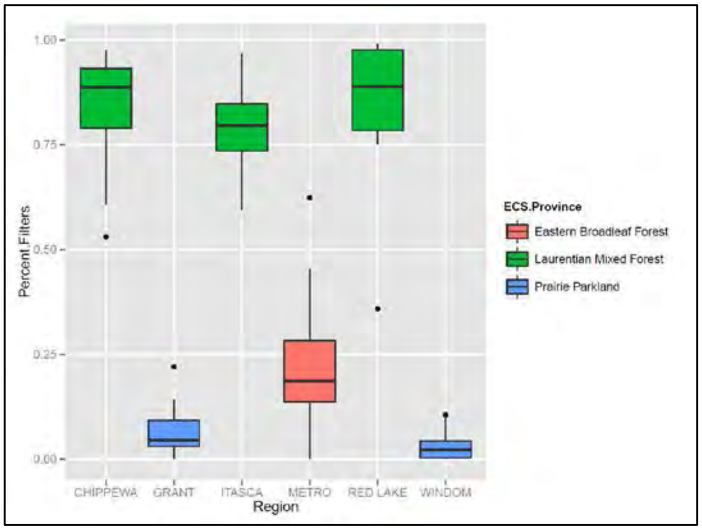

Figure 4. Boxplots for percent filters by ECS Province and Region.

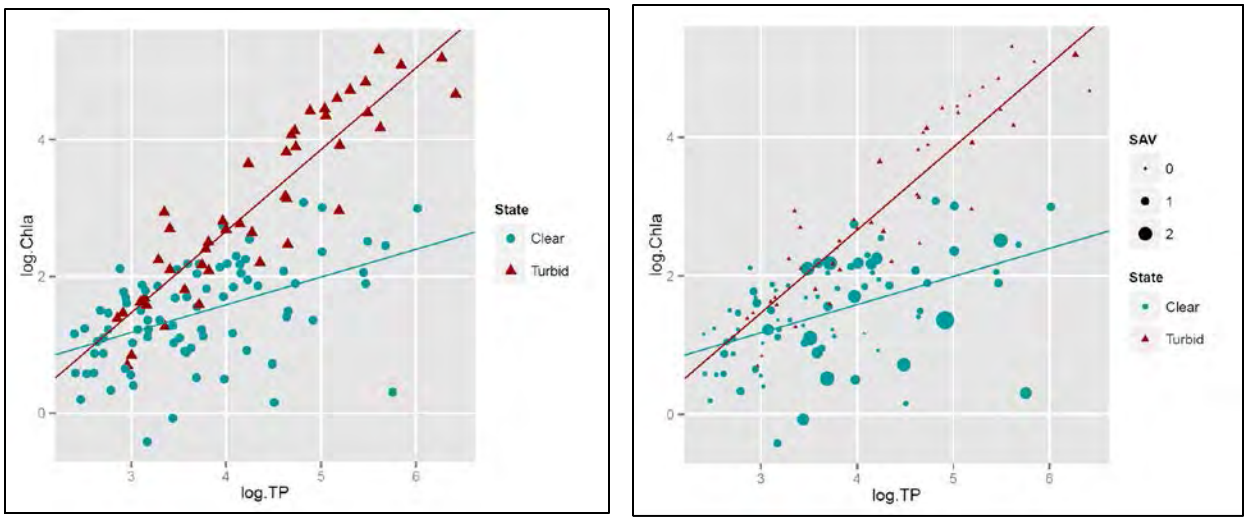

Figure 5. Log(Chla) vs. log(TP) for year 2009. Lake classifications are distinguished by color and shape and state-dependent regression lines are distinguished by color. The right figure is the same as the left but with point size proportional to SAV mass.

DISCUSSION

The three best predictors of TP included the percentage of filters in the upstream watershed of each lake, benthivore mass, and lake depth. While the significance and influence of these three predictors is not surprising, it is perhaps unexpected that percent woodlands/ shrubs was a better predictor than percent disturbance or agriculture. Filter percentage was strongly correlated with disturbance percentage (r=-0.84), and thus these predictors explain similar patterns in the TP data. However, the percentage of woodlands/shrubs may be the best land cover predictor because in addition to being correlated with disturbance, woodlands and shrubs filter out P, reduce overland flow, and may be better indicators of historical land use (or lack thereof) compared to current presence of agriculture or human disturbance.

Results were not shown, but a significant positive interaction was found between depth and filter percentage. That is, the negative influences of depth and woodlands/shrubs on TP are mitigated as both depth and percent filters increase together. Perhaps this result is spurious or perhaps certain deep lakes in forested areas have unique characteristics that lead to higher TP levels, such as differences in soil or bedrock type. This relationship probably deserves further attention but is a good example of the difficulty of accounting for the multiple sources of P in lakes and the complex relationships that exist among driving variables.

For 2009 and 2010, lake classifications using the Bayesian latent variable regression framework were similar to those produced using the methods of Zimmer et al. (2009). An advantage of the Bayesian approach, however, is that it can capture uncertainty in the estimated state classifications. Additionally, because lake classification and regression estimation are done in an integrated framework, uncertainty in the classifications is propagated to the error of the regression coefficient estimates. Thus, we should obtain more realistic confidence bounds for the relationship between Chla and TP using the integrated Bayesian framework.

The Bayesian analysis may not have worked as well for year 2011 due to the presence of outliers and deep lakes with low TP, low Chla, and low SAV mass. Record precipitation was observed in Minnesota in the twelve months prior to July 2011 (NOAA National Climatic Data Center 2011), and lakes may therefore have been perturbed far from their steady states or have been in the process of transitioning. Additionally, SAV may not be useful for classifying very deep or very shallow lakes because low Chla levels and low SAV mass may be observed in deep lakes, and high SAV mass and high Chla levels can occur in very shallow lakes. Furthermore, others have demonstrated that depth affects the susceptibility of lakes to state shifts (Genkai-Kato and Carpenter 2005). Therefore, depth may be an important variable to consider in future analyses.

The two preliminary analyses presented here could eventually be incorporated into a management tool to assess the relative transition risks of different lakes. The TP model could be used to predict TP levels on the *x*-axis of Figure 5 depending on land use, depth, and benthivore mass. Once thresholds are identified in Figure 5, lakes can be compared based on their relative proximity to thresholds to aid in management decisions.

FUTURE WORK

Goodness-of-fit of the TP model needs to be evaluated, as well as its predictive ability. Additionally, we plan to explore possibilities for refining data inputs that would allow for variations in soil and bedrock types among the lakes to account for this additional source of P input. Such data may also help explain the significance of the interaction between depth and filter percentage.

To test the usefulness of the Bayesian latent variable regression approach to classify attracting states and estimate steady state relationships between Chla and TP, we will apply the method to data simulated from an ordinary differential equation (ODE) model that produces dynamics similar to those observed in shallow lakes (see Beisner et al. (2003) for a candidate model). We will also use the ODE model to better understand the implications of using TP as a surrogate for P input, especially in terms of the differences between the bifurcation diagram for Chla and P input (Figure 1) versus a phase plane for Chla and TP, and to help us determine an appropriate method for estimating nutrient thresholds. We plan to incorporate TP thresholds into the model to more easily obtain standard errors for threshold estimates, rather than attempt to estimate thresholds post-hoc. We also hope to explore using other measures of turbidity (NTUs for research lakes, Secchi depth for program lakes) in conjunction with Chla to separate out the non-algal components of turbidity, possibly similar to Wang et al. (2014).

Finally, the last two objectives, modeling state transitions between years and developing a tool to assess relative transition risk, will be addressed after further progress is made on the preliminary work presented here. Scientists and managers urgently need better means of predicting ecological transitions in shallow lakes, along with more formal strategies for assessing water-quality consequences of watershed conversions. We think the current research is an important step toward improving management of shallow lakes and toward more productive conservation planning efforts for both shallow lakes and adjacent upland watersheds.

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EVALUATING THE SUCCESS OF THE MINNESOTA PRAIRIE CONSERVATION PLAN: CHALLENGES AND LESSONS LEARNED USING WATERFOWL AS A CASE STUDY

James B. Berdeen

SUMMARY OF FINDINGS

The Minnesota Prairie Conservation Plan (MPCP) established 36 Core Areas to protect, restore, and enhance grasslands, wetlands, and other habitats in the Prairie and Prairie – Forest Transition areas. One measure of success outlined in the plan is a stable or increasing breeding population of mallards (*Anas platyrhynchos*) in Minnesota. I conducted a pilot study during 2014 in which the primary goals were to measure habitat use in Core Areas by mallards and other waterfowl and waterbirds, ascertain which metrics that could be used to measure success in the MPCP and the limitations and challenges associated with interpreting those metrics over space and time, and evaluate the feasibility of using ground-based wetland surveys to quantify the success of the MPCP in terms of populations of indicator species. Feasibility includes the ability to collect sufficient baseline data to precisely estimate population parameters for pairs and broods of waterfowl and waterbird species within Core Areas. A secondary goal was to use these estimates to rank Core Areas with respect to mallard habitat suitability to identify appropriate Core Areas for habitat enhancement projects.

I initially ranked Core Areas based on habitat characteristics (i.e., wetlands, grasslands) important to mallard pairs and broods. Personnel then conducted surveys at 403 wetlands within 11 Core Areas, and observed breeding pairs of 10 species of waterfowl and 1 waterbird during the pair period (4–25 June). Field crews also surveyed 265 wetlands within 8 Core Areas and observed broods of 12 waterfowl and 3 waterbird species during the brood period (25 June – 23 July). The most commonly observed species were mallards and blue-winged teal during the pair period, and Canada geese and hooded mergansers during the brood period. However, count data for all waterfowl and waterbird species were sparse, and there were zero counts at many wetlands. These data characteristics limited the opportunity to model and precisely estimate the population metrics, compare these estimates among Core Areas, and evaluate the covariate effects on the state and detection processes. Nevertheless, the modeling exercise was performed to gain an understanding of how models performed with the available data and how precisely parameters could be estimated.

Hierarchical models were built to examine how survey-, habitat-, and weather-related covariates influenced the detectability and wetland occupancy of mallard pairs and waterfowl broods, and generate estimates of these parameters. The top-ranked mallard-pair model suggested that occupancy varied among Core Areas, but these differences were not significant based on overlapping 95% confidence intervals. One strongly supported occupancy model for broods of all species aggregated suggested that this parameter was not influenced by any of the predictive covariates examined (i.e., a null model). The estimated wetland occupancy rates by mallard and blue-winged teal pairs were 8.9% and 5.5%, respectively. The estimated occupancy by broods of all waterfowl species aggregated was 29%. Unfortunately, differences in the occupancy of either mallard pairs or waterfowl broods of all species could not be discerned among Core Areas, in-part because of sparse count data and relatively few wetlands available to be surveyed from roadsides. It may be that anomalous weather (late spring and ice-out, followed by

above average monthly precipitation and heavy precipitation events) influenced the habitat condition to the extent that the spatial settling pattern of pairs and production of young also were affected.

After converting a wetland-level abundance metrics for both mallard pairs and waterfowl broods of all species to Core Area-level density using several approaches, these sites were ranked based on the latter parameter. Empirical ranks of Core Areas often were similar, but there were substantial differences between the predicted and empirical ranks of these sites.

My results suggest that it may be difficult to observe a sufficient number of mallard pairs or broods in Core Areas to assess whether the MPCP is achieving 1 indicator of success. Therefore, I highlight some of the challenges associated with evaluating the success of large-scale conservation and management projects (e.g., MPCP) and ways to improve the assessment of such projects. Such projects will require the establishment of realistic well-defined metrics of "success" that can be measured at the appropriate spatial and temporal scales, and at a reasonable cost. Further, more accurate spatial habitat data than was available for this pilot study is needed to increase both the efficiency of surveys and the accuracy of the calculations of the areal extent of important habitats.

Background and Justification

The Minnesota Prairie Conservation Plan (MPCP) was established in 2010 to protect, restore, and enhance grasslands, wetlands, and other habitats in the Prairie and Prairie – Forest Transition areas via joint efforts among government agencies, private organizations, and individuals. As part of this plan, 36 Core Areas interconnected by corridors were established. Several characteristics of prairie ecosystems are considered to be representative of properly functioning landscapes, and were chosen as measures of success for the MPCP. One indicator of success is a stable or increasing breeding population of mallards (*Anas platyrhynchos*) in Minnesota (Minnesota Prairie Plan Working Group 2011). This species was selected as an indicator because it uses upland habitats for nesting and wetlands for rearing broods.

To attain this goal, it is important to understand such phenomena as demographic characteristics that contribute most to mallard population growth and habitats associated with mallard population metrics. For example, demographic processes that operate during pairing and brood-rearing life-cycle phases, especially nest success and hen and duckling survival, appear to greatly influence the growth rate of the midcontinent population of mallards (Hoekman et al. 2002). Further, the area of temporary and seasonal wetlands is positively related to the abundance of mallard pairs in North Dakota and westcentral Minnesota (Krapu et al. 1997), and the logarithm of the ponded area of temporary, seasonal, and semi-permanent wetlands is positively associated with wetland occupancy by mallard broods in the Dakotas (Walker et al. 2013).

Knowledge of habitat components important to mallards during breeding and brood-rearing phases has been used in the development of conservation plans. For example, the Minnesota Long Range Duck Recovery Plan (DRP, Anonymous 2006) identified landscape-level habitat components that purportedly are positively associated with waterfowl production. This plan operates under the assumptions that greatest waterfowl production occurs within prairie-wetland complexes that are 10.4–23.3 km^2 (4–9 mi^2) in area, and are comprised of ≥40% grassland and ≥20% wetlands. Also, >50% of wetlands should be temporary and seasonal and there should be 1 shallow lake >20.2 ha (50 ac) on each habitat complex. The intent of the MPCP was to establish Core Areas with a similar composition of wetland and grassland habitats (Minnesota Prairie Plan Working Group 2011), but such habitat characteristics varied substantially among these sites (Table 1).

Because of recent interest in the determining the success of the MPCP (G. Hoch, MN DNR, personal communication), I initiated a pilot study to determine whether it was feasible to collect sufficient count data to precisely estimate abundance, density, and probability of wetland occupancy of pairs and broods of mallard and other waterfowl and waterbird species within MPCP Core Areas. Such data could be used to monitor population trends as a measure of success if this effort was conducted for a longer time period. Although MPCP Core Areas initially were selected because of existing native prairie, other grasslands, wetlands, and shallow lakes (Minnesota Prairie Plan Working Group 2011, p. 3). I expected a gradient of abundance metrics of pairs and broods of mallards, other waterfowl, and waterbirds that was attributable to site-specific differences in the area and composition of grasslands and wetlands (Table 1). More specifically, I expected that the ordinal ranking of Core Areas in terms of waterfowl abundance measurements to be positively associated with the corresponding habitat metrics, and that the differences in ranks of Core Areas could be useful for identifying site-specific habitat management needs.

The primary goals of this pilot project were to (1) measure the use of wetlands in MPCP Core Areas by mallards and other waterfowl and waterbirds, (2) critically examine which metrics that could be used to measure success in the MPCP and the limitations and challenges associated with interpreting those metrics over space and time, and (3) evaluate the feasibility of using ground-based wetland surveys to quantify the success of the MPCP in terms of populations of mallards and other waterfowl and waterbirds. In this study, feasibility included survey duration time, the selection and limitations of different study designs that could be used to survey wetlands in Core Areas; and whether sufficient data (i.e., sample sizes) could be collected to generate precise estimates of population parameters for comparisons over space and time.

Objectives

The specific objectives of this study were to:

(1) Rank the relative value of each MPCP Core Area to mallard pairs and broods based on knowledge of landscape-level habitat components that are important to these cohorts.

(2) Measure pair and brood use (presence-absence and abundance) of wetlands within Core Areas, and explain the variation in use based on several wetland- and landscape-level covariates.

(3) Estimate the *density* of pairs and broods of mallards and other waterfowl and waterbird species in Core Areas.

(4) Rank MPCP Core Areas based on empirical estimates of density and compare observed and predicted ranks to identify Core Areas that may not be functioning at expected levels with respect to a MPCP goal and guide future habitat-management projects (e.g., via predicted avian abundance-habitat relationships).

(5) Investigate the influence of survey-, habitat-, and weather-related covariates on detectability and use this information to improve survey protocols.

STUDY AREA

I conducted this study at a subset of MPCP Core Areas in the Prairie Parkland, Tallgrass Aspen Parkland, and Eastern Broadleaf Forest (Transition) ecological provinces (Figure 1).

METHODS

Site Selection

Originally, I planned to conduct surveys in the same Crew Areas during the pairing and brood-rearing phases of the study, and therefore predicted the value of Core Areas based on habitat characteristics important to both mallard pairs and broods, and acknowledged that the settling pattern of pairs likely would vary among years. Therefore, I stratified the 36 MPCP Core Areas by latitudinal zone (south, central, north), assigned 12 Core Areas to each zone, and numerically ranked these sites based on the composition of grassland and Types II-IV wetlands.

I then assigned the 12 Core Areas in each zone a class rank (high, medium-high, medium-low, and low) based on the corresponding numerical rank, and then randomly selected a Core Area from each latitudinal zone-class rank stratum (*n* = 12 Core Areas, Table 1, Figure 1).

Low counts of mallard pairs during the early phase of this pilot study forced a reconsideration of this approach to selecting sites at which to conduct brood surveys. Because of the need to observe a sufficient number of broods to both estimate wetland occupancy by this cohort and evaluate my methodology, I non-randomly selected 8 Core Areas (Table 2*b*, Figure 1) that likely had the greatest density of mallard broods.

Habitat Data

A GIS and pertinent data layers were used to quantify the areal extent of grassland and wetland habitats within each Core Area. Specifically, the MN DNR WMAs, CRP 2007, NLCD 2011, MN DNR Native Plant Communities, Big Stone NWR, BWSR, and NLCD 2011 layers (MN DNR, unpublished data) were used to calculate the areal extent of grasslands, and the Circular 39 Wetland data layer (MN DNR, unpublished data) was used to calculate this metric for wetlands. There are many grassland cover types in these GIS layers, but I used only those that were likely to attract nesting mallards in the GIS layer. My classification of wetlands followed Stewart and Kantrud (1971): temporary - ephemeral (Type I), temporary (Type II), seasonal (Type III), semi-permanent (Type IV), and permanent (Type V). All surveyed wetlands also were classified in the field according to Stewart and Kantrud (1971). I used the field classification if there was a discrepancy with the GIS classification.

Wetland Surveys

I divided the wetland surveys into 3 time periods based on the phenology of the mallard life cycle in Minnesota: migratory (29 April–28 May; migrants and breeding pairs were most likely to be counted), pair (4–25 June; focus was on counting pairs breeding locally, but broods that hatched early also were counted), and brood (25 June–23 July; focus was on counting broods, but adults were counted as well). During each period, field crews generally conducted surveys in the most southerly MPCP Core Areas first and then proceeded northward so that these efforts coincided with the appropriate mallard life-cycle phase of interest.

I chose to conduct surveys at Types I-V wetlands during the migratory and pair periods, but focused survey efforts on Types III-V wetlands during the brood period. I included Types IV and V wetlands during this study because (1) the alteration of many relatively small, ephemeral wetlands in Minnesota may have increased the use and value of relatively large, permanent wetlands to mallards (M. A. Hanson, Minnesota Department of Natural Resources [MNDNR], personal communication), and (2) these habitats are selected during the brood-rearing phase of the mallard life cycle (Raven et al. 2007, but see also Rotella and Ratti 1992). Personnel did not survey Type I wetlands and surveyed only a few Type II wetlands during the brood period because it was likely that these would be dewatered during summer and thus attract no ducklings. I used waterfowl surveys during the migration period to guide the survey methodology during the pair and brood periods. More specifically, I needed to develop an understanding of how many birds were likely to be detected per wetland and the time required to survey an adequate number of wetlands in a typical Core Area. Personnel attempted to survey as many wetlands in the selected Core Areas as possible during the pair and brood periods.

Personnel conducted wetland surveys using some of the methodology developed by Pagano and Arnold (2009*a*, *b*) and Walker et al. (2013). I attempted to maintain a relatively consistent field methodology throughout the study, but some differences occurred among the migration, pair, and brood periods as field techniques were being refined.

Personnel used a double-observer approach (Nichols et al. 2000) to conduct surveys. Birds were independently but simultaneously counted by 2 observers from both roadsides and by walking to wetlands (hereafter roadside and walk-in surveys, respectively) during all periods.

Roadside surveys were conducted at those wetlands that could be adequately observed from a public right-of-way, were not anomalous (e.g., quarry-pit wetland), or near a residence. Walk-in surveys were conducted at wetlands that could not be readily observed from public right-of-ways, were logistically feasible to access, were not anomalous, and to which field crews were permitted access (i.e., public and TNC lands). Both types of locations were surveyed to increase the number of wetlands examined and improve the representativeness of the wetland sample.

During surveys, personnel either stood at opposite ends of a vehicle (roadside) or stood 3–6 m away from each other (walk-in). Each observer used binoculars and a spotting scope to observe, identify, and count birds; and a Leupold ® RX-800/DNA rangefinders and a handheld compass to measure the distance and direction, respectively, to social groups and individual birds. The minimum duration of migrant and pair surveys was 2 min and brood survey was 10 min, but field personnel could conduct surveys for a longer time period if it was difficult to count all observable birds or if birds continued to emerge from vegetation during a survey. Personnel also conducted repeat-visit surveys (MacKenzie et al. 2006) during the brood period, with the 2 visits occurring within 4–36 hrs for a given wetland (Walker et al. 2013). A repeat-visit approach was used during the brood period because the detectability of this cohort is relatively low (e.g., Walker et al. 2013).

Personnel classified the social status of observed individual birds and aggregations of birds of 1 species as follows: group (>5 individuals, one or both sexes with no discernable pairs), flocked males (aggregations of ≤5), pairs, lone male, lone female, brood hen, and lone birds of unknown sex (see Dzubin 1969). Social groups that indicated paired breeding status were pairs, lone males, and flocked males (Dzubin 1969). Personnel classified the stage of development of ducklings based on feather development and body shape (Gollop and Marshall 1954). Bird counts, social classifications, development stages of ducklings, and distances and locations were recorded independently, but team members discussed their observations immediately after each survey to minimize species misidentifications and double-counts of birds, identify birds that were not detected by 1 observer, and reconcile discrepancies in assigned social classifications.

At the end of each survey, personnel also recorded the MPCP Complex name, date, survey location, observers, wetland type and identification number, ownership of land surrounding study wetlands (4 classes: public, private, The Nature Conservancy, mixed ownership), survey type (2 classes: roadside, walk-up), beginning and end times, weather variables (i.e., temperature, relative humidity, dew point, barometric pressure, wind speed and chill, heat stress index, precipitation, % cloud cover), and habitat characteristics (i.e., proportions of each study wetland that are covered along the edge by tall vegetation, proportion of the wetland observable from the survey point, proportion of the wetland that contained water [all 0–1.0 in 0.05 increments], whether or not the wetland was flooded beyond the normal edge). Locations of survey points were measured with Garmin ® Montana 650 GPS units. Most weather variables were measured with Kestrel ® 3000 Portable Weather Meters. Ocular estimates of *% cloud cover* and habitat characteristics were made jointly by crew members.

Data Analysis

First, the number of wetlands surveyed was summarized by type and period, and bird counts were summarized by MPCP Core Area, survey period, species, and social aggregation. This information was used to guide the selection of a response variable (*count* v. *occupancy*) for each species included in the modeling exercise, and to ascertain which waterfowl species and social aggregations (i.e., pairs, broods) had adequate information (i.e., number and distribution of detections) to include in this effort. Next, the distributional characteristics of predictive covariates were examined (see Giudice et al. 2012) to ascertain which should be transformed. These results along with findings of previous research, logic, and available sample sizes were used to ascertain which covariates were most likely to predict the detectability (p) and wetland occupancy (ψ) of breeding pairs and broods of each species or grouping of species. Detectability is defined as the probability that a cohort of interest was present, available for detection, and detected during a survey of a wetland; and occupancy is defined the probability that a wetland is occupied by a cohort of interest (Mackenzie et al. 2006).

The influence of survey-, weather-, and habitat-related (landscape and wetland spatial scales) covariates on p and ψ were examined to address a secondary research goal. The survey-related covariates examined were individual observer (OBS); survey method (roadside v walk-in, METHOD, categorical predictor); Julian date (JULDATE), the start time (24-hr, START) and duration of surveys (min, SURVDUR), and in surveys conducted during the brood period, wetland visit (first v. second during brood surveys; VISIT). The weather-related covariates were the wind speed (km/hr, WIND) and temperature (°C, TEMP) during each survey. Landscape-level habitat covariates were Core Area (COREA, categorical predictor), proportion of each Core Area comprised of medium-to-high quality grasslands (GRASS), and the density (per mi^2) of Wetland Types II-IV (DENSWET2-4) and V (DENSWET5) in each Core Area. The wetland-level covariates were Wetland Type (I–V, WETTYPE, categorical predictor); the proportions of wetland edges obscured by tall vegetation (TALLVEG); whether or not a wetland was flooded (FLOOD, categorical predictor); the ownership of land surrounding study wetlands (OWN, categorical predictor); the latitude of the survey point (LAT); and the proportion of the wetland area observable from the survey point (OAW, or observable area of wetland). The last covariate was developed as a surrogate measure of the surveyed area of a wetland basin, and is the product of the areal extent of a wetland (ac, measured in the GIS wetland layer) and a field estimate of the proportion of the wetland that is visible from the survey point. Because there was a strong positive skew in the OAW, it was necessary to log transform this covariate to improve its distribution. Log OAW was strongly correlated with the actual areal extent of wetlands, but the former covariate was a better metric for calculating the *densities* of birds and modeling the influence of the areal extent of survey area on the p and ψ.

Because of the low number of pair and brood detections in my data and the desire to examine the influence the many covariates on parameters of interest, a 2-stage approach was chosen to build models for both pairs and broods in separate analyses. In the first stage, a small set of *a priori* candidate models were developed to examine the influence of covariates on the observation process (detectability), and the state process (wetland occupancy) was held constant. All models were evaluated using information-theoretic methods, with candidate models having ΔAIC-values of ≤ 2 considered to have strong support relative to other models under consideration (Burnham and Anderson 2002). Further, I considered a covariate to be a significant predictor of p if it was included in the top-ranked model (Burnham and Anderson 2002) and the 95% asymptotic CIs associated with coefficient estimates of this covariate did not encompass 0.

The same structure of p from the best approximating model of the first stage continued to be used in the second stage, but the influence of several covariates on ψ was explored. As with the first stage, information-theoretic methods (Burnham and Anderson 2002) were used to identify the best approximating model, and 95% asymptotic CIs associated with each parameter in this model were examined to ascertain the precision of estimated covariate effects on ψ. The relatively strong support of a model does not indicate that it is necessarily reliable.

There were some differences in the analyses of data collected during the pair and brood periods. Both pair- and brood-count data were compiled as presence-absence data, but it was necessary to analyze these data somewhat differently. I treated the double-observation pair-count data generated by each member of a 2-person field crew at an individual wetland as that collected during independent visits. However, both double-observer and repeat-visit survey approaches were used simultaneously were used to count broods, so observations by each individual on a 2-person field crew were treated as 2 independent sampling occasions, and each of the 2 visits was treated as a different sampling period.

Pair-count data were sparse, so a preliminary data analysis was performed to identify those species that likely had sufficient observations to develop models and generate estimates. Brood-count data were especially sparse in some MPCP Core Areas, so data from only those Areas in which ≥10 wetlands were surveyed ≥2 times were included in the analyses. Species-specific brood-count data were aggregated into 3 biologically plausible groups: all waterfowl species, dabbling ducks, and cavity-nesting ducks. A separate set of analyses was performed on each of these groups.

Although a similar model-building process was used for both pair- and brood-count data, a slightly different set of candidate models were examined during both the first and second analytical stages for each cohort. Specifically, the model set for first stage of the pair analysis consisted of a null model in which ψ and *p* were held constant and other models in which habitat- (TALLVEG, OAW), weather- (TEMP, WIND), and survey-related covariates (SURVDUR) were used to predict *p*. In contrast, models in first stage of the brood analysis examined the influence of wetland- (TALLVEG, log OAW), weather- (WIND, TEMP), and survey-level covariates (OBS, START, METHOD, VISIT, SURVDUR) on *p*.

In the second stage of the pair analysis, several *a priori* candidate models were developed to examine the influence of wetland- (log OAW, TALLVEG, WETTYPE) and Core Area or landscape-level covariates (COREA, GRASS, DENSWET2-4, DENSWET5) on ψ. In the brood analysis, the influence of similar wetland- (WETTYPE, TALLVEG, log OAW), landscape- (COREA, GRASS, DENSWET2-4, DENSWET5), and survey-level covariates (JULDATE) on ψ were examined with a similar set of *a priori* candidate models.

I assumed no local extinction (ϵ) or colonization (γ) of pairs occurred during any survey, and therefore did not estimate these parameters during the analysis of data from this cohort. For broods, ϵ and γ were considered nuisance parameters because most repeat-visits to individual wetlands occurred within 36 h, and therefore the probabilities of these parameters were always modeled as constants. I define extinction as the probability that an initially occupied site will become unoccupied during the sampling period (i.e., detected on the first visit to a wetland but not the second), and colonization as the probability that a previously unoccupied site becomes occupied during this period (i.e., not detected on the first visit but detected on the second).

The R programming language (version 3.0.3, R Development Core Team 2014) was used to conduct all analyses. The R function “scale” was used to center and scale all covariates except log OAW and categorical predictors prior fitting models to data. Two functions in the R package “unmarked” (Fiske and Chandler 2011) were used to fit hierarchical models of occurrence and abundance to pair- and brood-count data and generate parameter estimates. Specifically, the “occu” function (MacKenzie et al. 2002, 2006; Royle and Dorazio 2008) was used to fit models to pair-count data, and the “colext“ function was used to fit dynamic-occupancy models (MacKenzie at al. 2003) to brood-count data.

Estimation of Pair and Brood Density

To meet the research goal of comparing the predicted and observed metrics of waterfowl abundance in MPCP Core Areas, it was necessary to estimate a parameter that could be extrapolated from the spatial scale of a surveyed patch (i.e., wetland) to that of the Core Area. Density fit that criterion, and was estimated in 2 ways for mallard pairs. First, the empirical estimate of density was computed as the sum of the count of indicated breeding pairs divided by the sum of the OAW in each Core Area. Second, a model-based density estimate was calculated by first modeling the wetland-level abundance of pairs as a function of individual Core Area, and incorporating the influence of survey duration and proportion of tall vegetation on detectability into the model. The wetland-level predictions from this model were summed across all of these habitat units in a given Core Area, and then divided by the OAW following the same approach as the empirically based estimate of density. The model was fit in R using the "multinomPois" function (Royle 2004, Royle and Dorazio 2006) in the unmarked package. I only used a wetland-based empirical estimate of brood density, calculated as sum of the counts of broods divided by the sum of the OAW for a given Core Area (broods / survey ac). There was no attempt made to generate model-based estimates of density because brood-count data were sparse and there was great uncertainty associated with model-based estimates of occupancy.

Both pair and brood density were calculated at the spatial scale of the Core Area. Specifically, the number of pairs or broods per OAW in a given Core Area was multiplied by the total area of Type II-V wetlands in that site, and this value was divided by the total area (mi^2) of that site. This can be interpreted as a crude index of pair or brood density at the Core Area scale, and is referred to as the total area-based empirical approach.

Ranking MPCP Core Areas

I first developed predictive ranks of MPCP Core Areas for mallard pair and brood cohorts separately. The predictive ranking of Core Areas for pairs and broods were based on the proportions of these spatial units comprised of Type II–IV wetlands and grassland habitats of moderate-to-high quality to nesting waterfowl, respectively. I then produced empirical ranks of each Core Area based on the relative values of each approach used to estimate density of the cohorts of interest.

RESULTS

I did not analyze data from the migration period because field methodology still was being developed at that time. Survey data are available from 403 wetlands in 11 MPCP Core Areas examined during the pair period and 265 wetlands in 8 Core Areas during the brood period. I tabulated the number of wetlands surveyed by type, MPCP Core Area, and period (Table 2).

Roadside surveys comprised 83% and 87% of wetland surveys during the pair and brood periods, respectively, and walk-in surveys comprised the remainder. The wetlands surveyed during the pair period were mostly on private (68%) and public (24%) land, but some were located on mixed ownership (5%) and The Nature Conservancy (2%) properties, and 1% occurred on lands in which the ownership was not known. During the brood period, 71% of surveys were conducted on private land, 25% on public land, and 4% on wetlands surrounded by properties of mixed ownership. Water levels could not be adequately observed at some study wetlands, usually because of dense vegetation. Of the wetlands that could be observed adequately during the pair and brood surveys, field crews estimated that flooding was occurring at 14% and 7% of wetlands, respectively.

I included 352 of the 403 wetlands examined during the pair period in the analyses. Some wetlands were excluded because of a dewatered condition or missing covariate data. The MPCP Core Areas that met the criterion of ≥10 wetlands surveyed twice during the brood period were: Big Stone Moraine, Glacial Lakes, Lac qui Parle Prairie, and Lake Christina Hills. Data from 250 of the 265 wetlands surveyed during the brood period were included in the analyses.

After initially aggregating bird observations into 8 social classifications, I reclassified some of these groupings as indicated breeding pairs and broods for the analyses. I then tabulated counts of these 2 cohorts by species, MPCP Core Area, survey period, and proportion of surveyed wetlands with the cohorts of interest (Table 3). Personnel observed 10 waterfowl and 1 waterbird species in pairs during 4 – 25 June, and 12 waterfowl and 3 waterbird species with broods during 25 June – 23 July (Table 3).

Most wetlands had ≤1 indicated breeding pair of mallards (Figure 2) or blue-winged teal (*Anas discors*, Figure 3) or broods of all species (Figure 4). Further, the proportions of wetlands with pairs of any species during 4–25 June or broods of any species during 25 June – 23 July were low (Table 3). The number of observations of the target cohorts of all species was too sparse to develop reliable models, especially for broods of any individual species. Nevertheless, the modeling exercise was conducted to gain an understanding of how models performed with the available data and how precisely parameters could be estimated. Relatively simple models were developed for the pairs of the 2 most abundant species, as well as aggregations of 3 species groups of broods: (1) all observed waterfowl (i.e., mallard, blue-winged teal, American green-winged teal [*Anas crecca*], gadwall [*Anas strepera*], northern shoveler [*Anas clypeata*], ring-necked duck [*Aythya collaris*], canvasback [*Aythya valisineria*], redhead [*Aythya americana*], lesser scaup [*Aythya affinis*], unidentified scaup [*Aythya sp.*], hooded merganser [*Lophodytes cucullatus*], wood duck [*Aix sponsa*], large Canada goose [*Branta Canadensis maxima*], trumpeter swan [*Cygnus buccinator*]), (2) dabbling ducks, species of the genus *Anas* (i.e., mallard, blue-winged teal, American green-winged teal, gadwall, northern shoveler), and (3) cavity nesters (i.e., hooded merganser, wood duck).

Density and Ranks of MPCP Core Areas

The calculated density of mallard pairs in different Core Areas ranged from 0 to 39.10 pairs/mi^2 using the data-based approach. In the model-based approach, density estimates of this cohort ranged from 0 to 107.31 pairs/mi^2. In the first approach to calculating the density of broods of all waterfowl species combined, estimates for different Core Area ranged from 0 to 0.27 broods/surveyed acre of wetland. The second approach produced density estimates of 0 to 35.87 broods/mi^2 in the Core Areas examined.

Rankings of these Core Areas based on the relative value of these density calculations are presented in Table 4, as are the ranks of these sites generated from predicted ranks (i.e., those based on the proportion of Core Areas comprised of wetlands and grasslands). The predicted ranks of Core Areas often were substantially different than empirically-based ranks for both cohorts. In contrast, rankings of Core Areas based on the 2 different methods of calculating density of each cohort often were qualitatively similar.

Pair Detection

Pairs of 2 waterfowl species, mallards and blue-winged teal, had sufficient count data with which to perform analysis. The best approximating model in the first analytical stage indicated that *detection* of mallard pairs was influenced by log survey duration, log wind speed, log observable area of wetlands, temperature, and the proportion of wetland edges obscured by tall vegetation (Appendix 1*a*). However, the associated coefficient estimates of only 2 covariates, log survey duration and the proportion of wetland edges obscured by tall vegetation, did not encompass 0. Log survey duration had a positive influence on detectability (Figure 5), but the proportion of wetland edges obscured by tall vegetation had a negative influence (Figure 6). Consequently, an *a posteriori* model in which p varied by log survey duration and the proportion of wetland edges obscured by tall vegetation and ψ was constant was developed and compared to other candidate models in an information-theoretic framework (Appendix 1*a*). This model was ranked higher than any *a priori* model.

In the first stage of the analysis of blue-winged teal pair data, only 1 approximating model that had relatively strong support (Appendix 2*a*). This model indicated that detectability was positively associated with log survey duration (Figure 7).

Overall estimates of the detectability of mallard and blue-winged teal pairs also were generated. These estimates are 0.912 (95% CI: 0.800–0.964) and 0.848 (95% CI: 0.669–0.940), respectively.

Brood Detection

Because few broods of any species were observed during 25 June – 23 July (Table 3) and these count data were not well-distributed across Core Areas or predictive covariates, it is unlikely that there was sufficient data to build reliable species-specific models. Therefore, species-specific count data were aggregated into 3 groups (i.e., all waterfowl species, dabbling ducks, and cavity nesting ducks) and separate analyses were performed on each.

In the first stage of analyses of brood data from all observed waterfowl species combined, the best approximating model (Appendix 3*a*) indicated that detectability was negatively associated with wind speed (Figure 8) and temperature (Figure 9), but positively associated with log OAW (Figure 10) and whether a brood was detected on a previous visit. Specifically, the detectability of broods was slightly greater on the second visit (1.00, 95% CI: 0.00–1.00) if it was detected on the first (0.926, 0.539–0.964). Detectability also varied by method (Figure 11), with greater estimates generated during roadside surveys than walk-in surveys.

There was no evidence that the covariates examined influenced the detectability of dabbling duck broods (Appendix 3*c*). The overall estimate of this parameter in the null model was 0.89 (95% CI: 0.76–0.95).

The analysis of cavity-nesting species suggested that detectability was negatively associated with temperature and wind speed, but positively associated with log OAW and whether a brood was observed at a wetland on the first of 2 visits (Appendix 3*e*). Detectability also varied by survey method, with a greater proportion of broods detected during roadside surveys than during walk-in surveys.

Detectability estimates of the broods of 6 species with adequate data also were generated using only double-observer data. These species-specific estimates are: mallard 0.769 (95% CI: 0.548–0.902), blue-winged teal 0.780 (95% CI: 0.611–0.889), hooded merganser 0.845 (95% CI: 0.844–0.954), large Canada goose 0.892 (95% CI: 0.784–0.950), wood duck 0.918 (95% CI: 0.812–0.967), and pied-billed grebe 0.930 (95% CI: 0.798–0.978). The substantial overlap of the 95% CIs associated with these point estimates suggests that there was no evidence of species-specific differences in detectability.

Pair Occupancy

Based on results of the first stage of analyses, I considered the covariates log survey duration and proportion of wetland edges obscured by tall vegetation to be important predictors of the detectability of mallard pairs (Figures 5 and 6, Appendix 1*a*). Consequently, these covariates were used as predictors of detection in efforts to model wetland occupancy. Two candidate models had relatively strong support, with ΔAIC-values of ≤2 (Appendix 1*b*). The top-ranked model indicated that occupancy varied among MPCP Core Areas, but the 95% CIs associated with these point estimates overlapped substantially (Figure 12). The second-ranked model indicated that occupancy was positively associated with the proportion of Core Area comprised of grassland but negatively associated with the density of Type V wetlands. The density of Type II–IV wetlands also influenced occupancy under this model, but the 95% CIs of the coefficient estimate of this covariate encompassed 0, so I could not make an inference about the relationship between this habitat attribute and the occupancy of mallard pairs.

In the second analytical stage of blue-winged teal pair data, log survey duration was used as a predictor of detection in the modeling of wetland occupancy (Figure 7, Appendix 2*a*). The only model with relatively strong support indicated that the probability of occupancy varied among MPCP Core Areas (Appendix 2*b*). However, this parameter was inestimable for some Core Areas, probably because observational data for this species were sparse. Thus, I will not discuss the relative rankings of Core Areas from the perspective of blue-winged teal pairs.

Overall estimates of occupancy for both mallards and blue-winged teal also were generated. These estimates are 0.089 (95% CI: 0.063–0.123) and 0.055 (95% CI: 0.035–0.085) for mallard and blue-winged teal pairs, respectively.

Brood Occupancy

In the second analytical stage of brood data from all observed waterfowl species aggregated, 4 candidate models had relatively strong support (Appendix 3*b*). Two models indicated that occupancy indicated that wetland type was an important influence on this parameter. I consider the second-ranked model, which indicated that wetland occupancy was constant, to be of most interest because it had 2 fewer parameters than the top-ranked model and a ΔAIC-value of only 1.2. The overall probabilities of occupancy, extinction, and colonization were 0.29 (95% CI: 0.23–0.36), 0.38 (95% CI: 0.27–0.50), and 0.10 (95% CI: 0.05–0.16), respectively. The estimate of wetland occupancy used data from the 4 Core Areas with a sufficient number of wetlands surveyed (Figure 13).

Two models in the analyses in which all observed dabbling duck species were aggregated had ΔAIC-values of <2, and thus had relatively strong support (Appendix 3*d*). The top-ranked model indicated that wetland occupancy was negatively associated with the proportion of grassland in Core Areas, but positively associated with the density of Type II–V wetlands. The second-ranked model had a similar ΔAIC-value and the same number of parameters as the top-ranked model, but better addressed the research objective of discerning differences in wetland occupancy among Core Areas. Wetland occupancy estimates in Core Areas ranged from 0 (95% CI: 0.00–0.01) to 0.21 (95% CI: 0.11–0.37), and probabilities of extinction and colonization were 0.49 (95% CI: 0.26–0.72) and 0.03 (95% CI: 0.01–0.06), respectively.

The top-ranked model in the analyses of cavity-nester broods indicated that wetland occupancy was positively associated with log OAW and the proportion of the wetland edge obscured by tall vegetation, but negatively associated with the proportion of grassland in the Core Area and the density of Types II-IV wetlands (Appendix 3*f*). The second- and third-ranked models were competitive because both had ΔAIC-values of only 0.53 and had 2 fewer parameters than the top-ranked model. However, I preferred the third-ranked model because it used the covariate Core Area to explain variation in occupancy, which allowed the discernment of differences among sites. Further, the negative relationship between occupancy and wetland density in the top-ranked model appeared spurious. Occupancy estimates in the preferred model ranged from 0.05 (95% CI: 0.01 0.19) to 0.23 (95% CI: 0.16–0.32) among Core Areas, and the estimates of extinction and colonization were 0.33 (95% CI: 0.20–0.50) and 0.06 (95% CI: 0.03–0.11), respectively.

Weather

Statewide ice-out dates were 9 d later than the long-term median date (MNDNR 2015*b*). Monthly weather characteristics during the study indicate that many MPCP Core Areas were located in divisions that were slightly cooler and had greater precipitation than normal during much of the field season (Table 5, MNDNR 2015*a*). Rainfall amounts during June 2014 were approximately 3 times greater than normal (MNDNR 2014*b*). A heavy rainfall event occurred in substantial portions of Minnesota during 11–12 May 2014 (MNDNR 2014*a*).

DISCUSSION

Challenges of Assessing MPCP Success

A primary goal of MPCP is to protect, restore, and enhance grasslands, wetlands, and other habitats in the prairie and transition zones (Minnesota Prairie Plan Working Group 2011). Unfortunately, current and accurate land-cover data were not available during this study.

Similarly, the dates, locations, and areal extents of all prior and planned habitat restoration and enhancement efforts in each of the 36 Core Area and associated corridors had not been incorporated into a central database. Such data is needed as a baseline for planning surveys and evaluating the current indicators of success of the MPCP, in terms of both of (1) habitat preservation and improvement and (2) ecosystem function.

The lack of accurate spatial data also hindered my efforts to select a representative sample of wetlands for surveys, decreased the efficiency of surveys (e.g., some wetlands displayed in the Circular 39 GIS layer were dry or had been altered to the extent that a new classification was warranted), and did not facilitate the accurate calculations of the areal extent of important habitats, association of habitat attributes to avian-count metrics, or extrapolation of count data from wetlands to Core Areas. I did not classify terrestrial habitats as part of the survey methodology, and therefore did not detect problems with the available grassland habitat data. However, it is likely that the areal extent of grassland habitats in MPCP Core Areas was less than that indicated by the GIS layer, given the large-scale conversion of grasslands to croplands (Lark et al. 2015) and recent decrease in the area enrolled in the Conservation Reserve Program (MacDonald 2013).

It would be beneficial to periodically evaluate the success of the MPCP to provide useful feedback on the responses of populations of indicator species to management actions, but the selected measures of success must be realistic, measurable, and biologically meaningful. However, a current measure of related to ecosystem function (i.e., stable-to-increasing populations of indicator species at the statewide level [Minnesota Prairie Plan Working Group 2011, pp. 47–48]) appears unrealistic because it is unlikely that management actions on Core Areas (about 3% of the land base of Minnesota) could substantially influence population trends at a statewide scale. Further, any assessment of the population responses of migratory species to management actions could be confounded by functional processes that occur at multiple spatial and temporal scales. Preferably, baseline population estimates of indicator species would have been estimated and the areal extents of important habitats, prior habitat management activities, and administrative actions (e.g., protection, restoration, creation, enhancement) would have been measured accurately at the time Core Areas and Corridors were established, and then periodically assessed as restorative efforts occurred. These measurements were not taken, so alternative approaches must be used to evaluate the success of the MPCP. This could be accomplished by comparing population parameter estimates of indicator species within managed sampling units (i.e., treatments) located inside Core Area to those outside the boundaries.

I initiated a pilot study to measure the use of wetlands in MPCP Core Areas by waterfowl, and examine the feasibility of using the mallard populations at these sites as an indicator of success under the MPCP. Field crews surveyed 403 wetlands during the pair period and 265 wetlands during the brood period across a broad geographic area within Minnesota to try to meet these goals, but counts of mallards and other waterfowl and waterbirds (Table 3) were substantially lower than I anticipated. Sparse count data of some indicator species could arise in a broad-scale wildlife-monitoring program designed to assess the performance of conservation efforts. That I was able to document pairs of 18 species and broods of 15 species of waterfowl and waterbirds using Core Areas (Table 3) supports the idea of conserving and improving habitats at these sites. However, avian habitat use during 1 field season does not provide information regarding the specific demographic vital- rates influencing site-specific population dynamics. The most important findings of this pilot project may be (1) it is challenging to collect sufficient mallard pair and brood count data over a set of Core Areas that vary in size, shape, habitat composition, and accessibility, and (2) there are challenges and limitations to using migratory species count-data as a measure of program success.

A major challenge of the MPCP that will need to be addressed is the development of a more realistic set of program goals. This need is indicated by the following observations. First, it is unlikely that habitat restoration and management activities that occur on 3% of the Minnesota land base would drive the statewide population growth of mallards. Second, any assessment of program success based on population levels or trends of indicator species that are migratory likely will be confounded by the influence of variables that operate during the non-breeding season and outside of the Core Areas. Third, pair- and brood-count data collected during 1 field season from a subset of available wetlands may be difficult to interpret and therefore not provide the information needed to adequately evaluate success, given the lack of baseline population and reliable spatial habitat data.

To develop a set of more realistic set of population goals for indicator species, researchers will need to identify a parameter that can be readily estimated at a reasonable cost. The use of the parameter density (number of cohorts / unit area) to compare Core Areas is appealing because it can be extrapolated from the spatial scale of wetlands to that of Core Areas, which permits the comparison of larger spatial units that vary greatly in areal extent and shape. However, this parameter is difficult to reliably estimate because precipitation and evapotranspiration substantially will alter the areal extent of wetlands during the survey period, and the obscuring effects of dense vegetation and topography will not permit observers to estimate the areal extent of wetlands at the time of surveys. Because I typically generated counts of 0 or 1 pair or broods at most wetlands, it was preferable to measure a binary abundance metric (i.e., presence-absence) for these cohorts and estimate wetland occupancy adjusted for imperfect detection. Occupancy modeling based on repeated surveys has become a popular monitoring tool, especially for relatively rare species (see MacKenzie et al. 2006), but the use of this parameter to measure success of the MPCP is not necessarily straightforward. For example, 2 Core Areas with an equal areal extent of wetlands and waterfowl detectability, immigration, and emigration may have an equal number of pairs and broods during year 1. If 1 Core Area has average hen and duckling mortality but the other has unusually high mortality of these cohorts, it is intuitive that the second Core Area likely would have lower abundance in year 2 (assuming equal immigration and emigration between sites and years) and would not contribute to the MPCP goal of a stable-to-increasing statewide mallard population. Using occupancy or density to monitor success of the MPCP is further complicated by differences in habitat composition and accessibility among Core Areas, the annual fluctuation in areal extent in Type I-III wetlands attributable to climactic variation, and other factors operating at multiple spatial scales (e.g., wetland, landscape, regional) that affect the spatial distributions of waterfowl population.

Using statewide population trends of an indicator species may not be a realistic means of ascertain the success of the MPCP. It may be more tractable to examine differences in population parameter estimates among smaller sample units (e.g., Core Areas, control and habitat treatment sites within Core Areas) as a way of ascertaining success. However, it will be necessary to measure parameters of interest over a realistic timeframe because a staggered response-time of populations to management actions is likely, local waterfowl populations often fluctuate, and the many variables that influence the local population dynamics of migratory species operate at multiple spatial and temporal scales.

Researchers should consider the trade-offs associated with various sampling designs, survey methodologies, sample size needs, and project costs when attempting to ascertain the success of large-scale conservation projects, such as the MPCP. For example, there was a trade-off between the number of wetlands sampled, the number of visits to study wetlands, and costs in this pilot study. If estimating temporal trends in occupancy was an objective in a longer-term study, there also would be a tradeoff between the study length (i.e., field seasons) and the number of wetlands sampled. In a situation such as that I encountered (i.e., reasonably high detection probabilities but only low-to-moderate occupancy probabilities), researchers should survey a greater number of wetlands per Core Area, as opposed to more intensively sampling fewer wetlands. Unfortunately, it would be difficult to survey enough wetlands in smaller or drier Core Areas to generate precise estimates of wetland occupancy.

Despite the effort and resources expended on this project (i.e., 3 2-person crews each using a vehicle for 3 months) and surveys conducted at many of the accessible roadside wetlands in selected Core Areas, precise estimates of occupancy could not be generated. MN DNR personnel surveyed 403 wetlands during the pair period (4 – 25 June) and 265 wetlands during the brood period (25 June – 23 July), but researchers in the Dakotas were able to visit more wetlands and count more waterfowl, probably because the densities of both were substantially greater in the Dakotas than in MPCP Core Areas. Specifically, a 2-person team surveyed 1182 wetlands for pairs during 3–18 May (Pagano and Arnold 2009*a*), and later surveyed 787 wetlands for broods in North Dakota during 2–25 June and 2–25 July of 1 field season (Pagano and Arnold 2009*b*) and an unspecified number of field crews surveyed 3,226 wetlands in the Dakotas for broods during 3 field seasons (Walker et al. 2013). MN DNR crews observed only 54 mallard and 30 blue-winged teal pairs during the pair period, and 12 mallard and 21 blue-winged teal broods during the brood period, but Pagano and Arnold (2009*a*) detected 656 mallard and 1066 blue-winged teal pairs during 3–18 May, and Pagano and Arnold (2009*b*) observed 306 mallard and 503 blue-winged teal broods during 2–26 June and 2–26 July. Sufficiently precise wetland occupancy estimates for larger Core Areas could have been generated by surveying more wetlands, but costs would have increased substantially.

MPCP Core Area Rankings Based on Density Estimates of Mallard Pairs and Waterfowl Broods

I report both the predicted and empirical ranks of Core Areas, but these rankings should be viewed with skepticism. The predicted ranks were based on scientific knowledge of mallard habitat associations (see Krapu et al. 1997, Walker et al. 2013), but some empirical ranks were based on density estimates calculated from sparse count data, Core Areas with relatively few wetlands, and subjective estimates of the observable area of study wetlands. Further, both predicted and empirical rankings were based on measurements of the areal extent of important habitats (i.e., wetlands, grasslands) that are of questionable accuracy. Consequently, my initial rankings of Core Areas should not be used to guide habitat management projects.

Density estimates of mallard pairs calculated from the data-based approach (range 0 to 39.10 pairs/mi^2) appeared more plausible than the model-based approach (0 to 107.31 pairs/mi^2). Although the spatial areas of inference are not the same and survey methodologies are dissimilar, the density of mallard pairs in the Four Square Mile Surveys (range: 1.5 to 5.8 mallard pairs/mi^2, Anonymous 2014) was similar to some but not all of my Core Area density estimates. The model-based pair-density estimate at one small Core Area (Rush Lake) appeared to be spurious. This result may have generated from a relatively high count of pairs on the few wetlands accessible to field crews. Unfortunately, it is not possible to make a meaningful comparison between my estimates of young-of-the-year density because the density metrics used by the 2 surveys were different (broods/mi^2 v recruits/ mi^2).

It is interesting that the different methods used to empirically estimate density generally produced similar ranks of Core Areas (Table 4), but that the predicted ranks in some cases were substantially different than empirically-based ranks. It may be that differences between predicted and empirical ranks occurred because (1) the habitat variables important to mallard pairs and broods in other locations were not useful for predicting the abundance or wetland occupancy of these cohorts in western Minnesota, or my ranking system was not refined enough to capture factors influencing mallard settling or reproductive success, (2) the habitat information garnered from available wetland and grassland GIS layers was inaccurate and therefore not useful for making predictions, or (3) unusual weather patterns immediately prior to and during the field season (MNDNR 2014*a*, *b*; 2015*a*, *b*) may have contributed to unexpected spatial distributions of settling pairs of mallards and the low production of waterfowl broods.

Modeling and Estimation of Occupancy

The results of modeling and estimation efforts should be viewed with caution for several reasons. Field crews were able to count pairs and broods at fewer wetlands within Core Areas than some recent studies (e.g., Pagano and Arnold 2009*a*, *b*; Walker et al. 2013), and this sparse data did not facilitate the reliable estimation of occupancy. Also, multiple candidate models in most analyses that had ΔAIC-values ≤2 (Appendices 2–4), which suggests the existence of substantial modeling uncertainty. Last, data were collected during a field season with an anomalous weather pattern (MNDNR 2014*a*, *b;* 2015*a*, *b*), which likely affected the spatial distribution patterns of the settling pairs and the survival and thus abundance of clutches and young. Thus, it may be necessary to conduct waterfowl surveys in Minnesota for multiple field seasons to obtain sufficient data to accurately estimate occupancy.

Pair Occupancy

The top-ranked mallard-pair model suggests that wetland occupancy varied among MPCP Core Areas, but there was no significant difference among most of the site-specific estimates of this parameter. The top-ranked blue-winged teal-pair model suggests that wetland occupancy is associated with both landscape- (proportion of grassland, densities of Types II-IV and Type V wetlands in each Core Area) and wetland-level covariates (the proportion of the wetland area observable from the survey point, the proportion of wetland edge obscured by tall vegetation, wetland type). The inability to detect significant differences in wetland occupancy rates of pairs among Core Areas may be attributed to the relatively small pair counts (*n* = 54 mallards and 30 blue-winged teal [Table 3], with overall wetland occupancy estimates of 8.9% and 5.5%, respectively). The low pair-count data also may be attributed to the somewhat late timing of my surveys; *i.e.*, some pair bonds may have ended and males may have moved to molting areas and thus were not available to be counted (Dzubin 1969) when surveys were conducted. Also, pair counts in the Core Areas may have been lower than anticipated because duck density in Minnesota probably is less than in the Dakotas (see Cordts 2015, Zimpfer et al. 2015). Last, low pair counts may have occurred in-part because none of the Core Areas surveyed met both the 20% wetland and 40% grassland criteria of the Duck Recovery Plan (Anonymous 2006, Table 1).

Brood Occupancy

There was substantial uncertainty with regard to the influences of different covariates on occupancy in any of my 3 aggregations of waterfowl species. This uncertainty may be attributed to sparse brood-count data and species-specific differences in niche occupation. Although some well-supported brood models suggest that the occupancy rates of the dabbling duck and cavity-nester aggregations differed among MPCP Core Areas, the substantial overlap of most 95% CIs associated with 4 of these site-specific parameter estimates suggest that differences were not discernable.

Detectability

Although modeling and estimating detectability usually is not a primary objective of waterfowl surveys, a precise and reliable estimate of this parameter is required to generate reliable estimates of wetland occupancy. Further, survey methodology could be improved and standardized with knowledge of the time during a survey at which detectability approaches 1.0, the approaches that generate sufficiently high estimates of this parameter, and knowledge of the environmental predictors that influence this parameter. For example, surveys targeting mallard and blue-winged teal pairs probably would generate detection probabilities of 1.0 at 12 and 17 min, respectively. Using the double-observer approach to count pairs also should produce high detectability estimates, given the estimates generated in this (91% and 85% for mallard and blue-winged teal pairs, respectively) and another study (91% for 8 waterfowl species combined [Pagano and Arnold 2009*a*]). Similarly, the use of both double-observer and repeat-visit surveys for broods allowed the indirect examination of the availability of broods to be counted, which is an important part of the observation process. This approach also permitted high estimates of brood detectability to be generated for both the first and second visits (93% and 100%, respectively) when this cohort was available to be observed on both visits. The type of survey conducted should be incorporated into models, given that greater brood detectability estimates are generated from roadside surveys than walk-in surveys (Pagano and Arnold 2009*b*, this study)

Habitat characteristics and weather attributes also may influence the detectability of waterfowl, and therefore should be measured and included as explanatory covariates in models. For example, my results and those of Pagano and Arnold (2009*a*) suggest that the proportion of wetland edges obscured by tall vegetation had a negative influence on the detectability of pairs (Figure 6), and a similar relationship was observed for waterfowl broods (Giudice 2001, Walker et al. 2013). This vegetative structure likely provides visual concealment and is commonly used as hiding cover by waterfowl. Researchers should consider excluding wetlands with especially dense emergent vegetation from their surveys (Nichols et al. 2000) because it is not feasible to count waterfowl using such habitats (see Giudice 2001).

The areal extent of surveyed wetlands also may have an effect on waterfowl detectability. Assuming a positive relationship between the observable area of wetland and the total area of the wetland, it appears that broods were more likely to be detected on relatively large wetlands (Figure 10). It may be that broods using larger wetlands were more tolerant of disturbance by field personnel than those using smaller wetlands; e.g., broods were less likely to move into hiding cover when personnel were present at larger wetlands. In contrast, 2 other studies observed a negative relationship between the detectability of broods and wetland size, but there likely were differences in the areal extents of wetlands between my study sites and those of Pagano and Arnold (2009*b*) and Walker et al. (2013). Further, I did not limit the size of wetlands examined, but Pagano and Arnold (2009*b*) only examined wetlands of ≤5 ha.

The weather covariates that influenced brood detectability varied among different waterfowl guilds (Appendix 3*a*, *c*, and *e*), but in the analysis of broods of all species combined, this parameter appeared to be affected by wind speed (Figure 8) and temperature (Figure 9). More specifically, wind speed likely had a negative influence on detectability because broods were obscured by the associated disturbance of the water surface and behavioral responses to this covariate (e.g., hiding from this disturbance in vegetative cover). Temperature may have negatively influenced detectability in several ways. Detectability could have been reduced when ambient temperatures were high if broods were less active or used shaded and concealed locations within wetlands, or if field personnel were fatigued or distracted by this condition. Walker et al. (2013) also observed a negative relationship between wind speed and the detection probability of gadwall and blue-winged teal. In contrast, Pagano and Arnold (2009*b*) found that wind speed and temperature were positively associated with detectability, but noted that this was dissimilar to results of other studies (e.g., Giudice 2001).

Researchers should conduct waterfowl surveys at the most appropriate time within their life cycle (e.g., when most observable) to increase the likelihood of generating representative count data for the cohorts of interest. Typical dates on which life-cycle phases occur at selected study sites usually are used to determine the timing of investigations, but there can be temporal variation in the phenology of some phases (e.g., Oja and Poysa 2007). Thus, it may be somewhat challenging to establish a sampling period *a priori* because of the difficulty in predicting annual variation in environmental conditions (e.g., weather patterns, phenology of ice-out) and its influences on the phenology of waterfowl life-cycles. It may be necessary to alter study plans when unusual environmental conditions occur to ensure that a sufficient number of waterfowl will be observed.

Personnel conducted pair surveys relatively late (4–25 June), in-part because of the late spring and ice-out dates of wetlands in Minnesota during 2014 (MNDNR 2015*a*, *b*) and the time required to complete surveys during the migration period. It may be that more waterfowl and waterbirds would have been observed during pair surveys conducted earlier (e.g., 3–18 May [Pagano and Arnold 2009*a*], 27 April–15 May and 20 May–6 June [Anonymous 2014]) because detectability likely decreased as emergent vegetation grew more densely during as the field season progressed. However, personnel also observed relatively few broods of any species, despite the substantial overlap between the dates of my brood surveys (25 June–23 July) and those of Pagano and Arnold (2009*b;* 2–26 June and 2–26 July) and Walker et al. (2013; 20 July–5 August). Thus, variables other than survey period (e.g., geographic pattern of settling pairs, seasonal weather) may have had some negative influence on the number of observed waterfowl at my study sites.

Researchers should conduct surveys when cohorts of interest are most detectable, which I expect is when waterfowl generally are most active (i.e., early morning, late evening). Reasonably high detectability estimates were generated in this pilot study, but few pairs and broods were observed during the typical survey hours (i.e., approximately 0700–1900). More birds may have observed if a greater proportion of the surveys were conducted only during the early morning and late evening. However, the obscuring effect of shadows and increased cost associated with mileage and travel time when driving to and from study sites twice per day must be considered if surveys are limited to these 2 periods. Further, the within-day temporal patterns of brood detectability may vary among species (Pagano and Arnold 2009*b*, Walker et al. 2013).

MANAGEMENT IMPLICATIONS

The establishment of MPCP Core Areas and Corridors could be an effective means of conserving and maintaining native prairie biotic communities and ecosystem processes, but this plan should be assessed (sensu Reynolds et al. 2001) periodically to ensure that goals and objectives are being met. However, results of this study indicate that an assessment of broad-scale conservation plans such as the MPCP will be complex. Such assessments could be simplified somewhat if the original objectives of the MPCP were replaced with metrics of success that were more realistic and easily measured. The development of new objectives and criteria to measure success will require critical thought by scientists and managers, and some knowledge of habitat conditions and the historical and current populations of indicator species in Core Areas. Further, there will be a need for monitoring programs to track the response of populations of indicator species to habitat management projects at the appropriate temporal and spatial scales. Identifying this temporal scale will require an understanding of the timeframe during which the population of interest is likely to respond to management actions. Selecting the best spatial scale at which to measure success may be especially challenging, in-part because of the need to develop and implement a waterfowl monitoring method that permits a meaningful extrapolation of population parameter estimates from the spatial scale of wetlands to that of Core Areas, which differ in total areal extent and in the composition, spatial configuration, and area of important habitats. It also will be a challenge to understand responses of low-density populations to habitat management, given that both pre- and post-treatment parameter estimates likely will have relatively wide 95% CIs.

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Table 1. The landscape-level habitat characteristics of Minnesota Prairie Conservation Plan (MPCP) Core Areas.

MPCP Core Area	Latitudinal Zone	Predicitive Class Rank [a]	Total area (mi^2)	Proportion Type II-IV wetlands [b]	Proportion grassland [c]
Antelope Hills	S	H	38.97	0.088	0.197
Lac Qui Parle Prairie [e]	S	H	166.72	0.107	0.219
Upper Minnesota River Valley	S	H	235.02	0.041	0.109
Chanarambie Creek [d]	S	MH	27.67	0.019	0.212
Prairie Coteau / Rock River	S	MH	38.61	0.037	0.116
Yellow Medicine Coteau	S	MH	24.99	0.035	0.15
Cottonwood River Prairies [d]	S	ML	7.63	0.055	0.12
Hole-In-The-Mountain	S	ML	70.83	0.023	0.116
Shaokatan Prairies	S	ML	16.83	0.021	0.144
Des Moines River Valley	S	L	135.81	0.016	0.081
Plum Creek	S	L	9.87	0.003	0.098
Red Rock Ridge [d]	S	L	19.08	0.005	0.09
Blue Stem Prairie	C	H	36.96	0.123	0.168
Felton Prairie [d]	C	H	42.86	0.149	0.235
Rothsay Prairie	C	H	35.35	0.202	0.34
Big Stone Moraine [d]	C	MH	35.76	0.108	0.157
Glacial Lakes [d, e]	C	MH	264.16	0.15	0.104
Waubun Prairie	C	MH	32.26	0.217	0.154
Lake Christina Hills [e]	C	ML	43.67	0.087	0.036
Big Stone Lake Prairie – North [e]	C	ML	14.81	0.045	0.174
Blanket Flower Prairie [c]	C	ML	11.77	0.02	0.189
Big Stone Lake Prairie – South [e]	C	L	17.45	0.014	0.183
Lake Traverse Prairie [e]	C	L	26.7	0.019	0.158
Reisdorah Prairie [d, e]	C	L	10.24	0.02	0.122
Aspen Parkland [d]	N	H	465.5	0.244	0.165
Glacial Ridge	N	H	185.36	0.173	0.156
Syre Prairie	N	H	31.5	0.152	0.248
Rush Lake [d]	N	MH	14.34	0.209	0.228
East Park - Thief Lake [d]	N	MH	139.72	0.131	0.079
Espelie	N	MH	10.026	0.374	0.12
Florian	N	ML	16.32	0.128	0.145
Pembina Prairie	N	ML	64.78	0.105	0.137
Wambach Santee Prairie	N	ML	71.35	0.08	0.135
Agassiz Dunes	N	L	41.54	0.053	0.097
New Solum Prairie [d]	N	L	39.87	0.147	0.073
Chester Hills Prairie	N	L	27.55	0.137	0.066

[a] H = high, MH = Medium-high, ML = Medium-low, L= Low

[b] The proportion of the total area of MPCP Core Areas comprised of Type II-IV wetlands (Stewart and Kantrud 1971) was estimated from the Circular 39 Wetland GIS layer.

[c] The proportion of MPCP Core Areas comprised of medium-to-high quality grasslands was estimated from the 2011 Cropland GIS layer.

[d] MPCP Core Area was examined during the pair period.

[e] MPCP Core Area was examined during the brood period.

Table 2. The number of wetlands of 5 types surveyed in Minnesota Prairie Conservation Plan Core Areas during 2 periods during the *a*) pair (4 – 25 Jun) and *b*) brood periods (and 25 Jun – 23 Jul) of 2014.

a) Period		Number of wetlands surveyed of 5 types [a]				
Pair (4 – 25 Jun)	Core Area	I	II	III	IV	V
	Aspen Parkland	26	30	20	2	39
	Blanket Flower Prairie			6		3
	Chanarambie Creek	1		8	1	4
	Cottonwood River	3	1	15	4	1
	East Park – Thief Lake	13	7	6	1	6
	Felton Prairie	1	5	12	1	3
	Glacial Lakes	7	9	31	15	12
	New Solum Prairie	4	14	11	3	2
	Red Rock Ridge			5	1	
	Reisdorah Prairie		1	9	2	1
	Rush Lake	1		16	3	4
Total		56	67	139	33	75
b) Brood (25 Jun – 23 Jul)	Big Stone Lake Prairie - North			1	2	1
	Big Stone Lake Prairie - South			5		
	Big Stone Moraine		1	22	9	7
	Glacial Lakes			62	42	24
	Lake Christina Hills			21	17	22
	Lake Traverse Prairie				1	2
	Lac Qui Parle Prairie		1	3	16	3
	Reisdorah Prairie			1	1	1
Total		0	2	115	88	60

[a] Wetland classifications followed Stewart and Kantrud (1971).

Table 3. Counts of the pair and broods cohorts of waterfowl and waterbird species observed during surveys conducted at Minnesota Prairie Conservation Plan Core Areas during the pair (4 – 25 Jun) and brood periods (25 Jun – 23 Jul) of 2014.

	Pair period (4 – 25 Jun)			Brood period (25 Jun – 23 Jul)		
Species [a]	# Pairs	# Broods	Proportion of wetlands with pairs	# Pairs	# Broods	Proportion of wetlands with broods
AGWT	4	0	0.005	2	2	0.008
BUFF	1	0	0.002	0	0	0
BWTE	30	1	0.057	40	21	0.057
CANV	0	0	0	2	4	0.015
COLO	4	0	0.010	4	2	0.008
GADW	0	0	0	15	1	0.004
HOME	2	3	0.005	11	48	0.147
LCGO	8	5	0.015	20	31	0.083
LESC	0	0	0	4	2	0.004
MALL	54	1	0.079	29	12	0.030
NSHO	8	0	0.012	3	0	0
PBGR	0	0	0	2	18	0.053
REDH	0	0	0	21	3	0.011
RNDU	17	0	0.020	15	2	0.008
RNGR	0	0	0	1	1	0.004
RUDU	0	0	0	10	0	0
TRUS	2	0	0.005	2	2	0.008
WODU	15	1	0.020	59	26	0.075

[a] Species-specific acronyms are: AGWT = American green-winged teal, BUFF = bufflehead, BWTE = blue-winged teal, CANV = canvasback, COLO = common loon, GADW = gadwall, HOME = hooded merganser, LCGO = large Canada goose, LESC = lesser scaup, MALL = mallard, NSHO = northern shoveler, PBGR = pied-billed grebe, REDH = redhead, RNDU = ring-necked duck, RNGR = red-necked grebe, RUDU = ruddy duck, TRUS = trumpeter swan, WODU = wood duck.

Table 4. The predicted, empirical, and model-based (pairs only) rankings of the value of a subset of Minnesota Prairie Conservation Plan Core Areas to mallard pairs and broods of all waterfowl species during the *a*) pair (4–25 Jun) and *b*) brood periods (25 Jun–23 Jul) of 2014.

Core Area	Region	Predicted rank	Empirical rank	Model-based rank
a. Pair period (4–25 Jun)				
Aspen Parkland	North	1	11	11
Rush Lake	North	2	3	1
Glacial Lakes	Central	3	8	8
Felton Prairie	Central	4	4	3
New Solum Prairie	North	5	7	6
East Park – Thief Lake	North	6	10	9
Cottonwood River	South	7	6	7
Reisdorah Prairie	Central	8	1	2
Blanket Flower Prairie	Central	9	5	5
Chanarambie Creek	South	10	9	10
Red Rock Ridge	South	11	2	4
b) Brood period (25 Jun–23 Jul)				
Lac Qui Parle Prairie	South	1	1	
Big Stone Lake Prairie – South	Central	2	7.5	
Big Stone Lake Prairie - North	Central	3	5	
Lake Traverse Prairie	Central	4	6	
Big Stone Moraine	Central	5	3	
Reisdorah Prairie	Central	6	7.5	
Glacial Lakes	Central	7	4	
Lake Christina Hills	Central	8	2	

Table 5. The monthly departure from normal measurements of temperature (°C) and precipitation (cm) of divisions[a] that encompass the Minnesota Prairie Conservation Plan Core Areas sampled during the 2014 field season.

Division [a]	MPCP Core Areas	Weather variable	Apr	May	Jun	Jul
Northwest	Aspen Parkland, Blanket Flower Prairie, East Park – Thief Lake, Felton Prairie, New Solum Prairie, Rush Lake	*Temperature*	-2.77	-0.50	+0.33	-1.17
		Precipitation	+4.60	-0.53	+6.53	-1.73
West-central	Big Stone Lake Prairie – North, Big Stone Lake Prairie – South, Big Stone Moraine, Glacial Lakes, Lac Qui Parle Prairie, Lake Christina Hills, Lake Traverse Prairie, Reisdorah Prairie	*Temperature*	-2.45	-0.67	+0.05	-1.61
		Precipitation	+3.43	+0.86	+9.73	-4.32
Central	Glacial Lakes	*Temperature*	-2.84	-0.83	+0.22	-1.44
		Precipitation	+7.52	+3.86	+11.20	-2.51
Southwest	Chanarambie Creek, Red Rock Ridge	*Temperature*	-1.73	-0.56	-0.11	-2.11
		Precipitation	-1.09	-3.53	+15.37	-4.37
South-central	Cottonwood River	*Temperature*	-1.55	-0.56	+0.27	-3.50
		Precipitation	+4.14	-3.73	+14.02	-5.44

[a] Division boundaries are available at: www.cpc.ncep.noaa.gov/products/analysis_monitoring/regional_monitoring/CLIM_DIVS/minnesota.gif

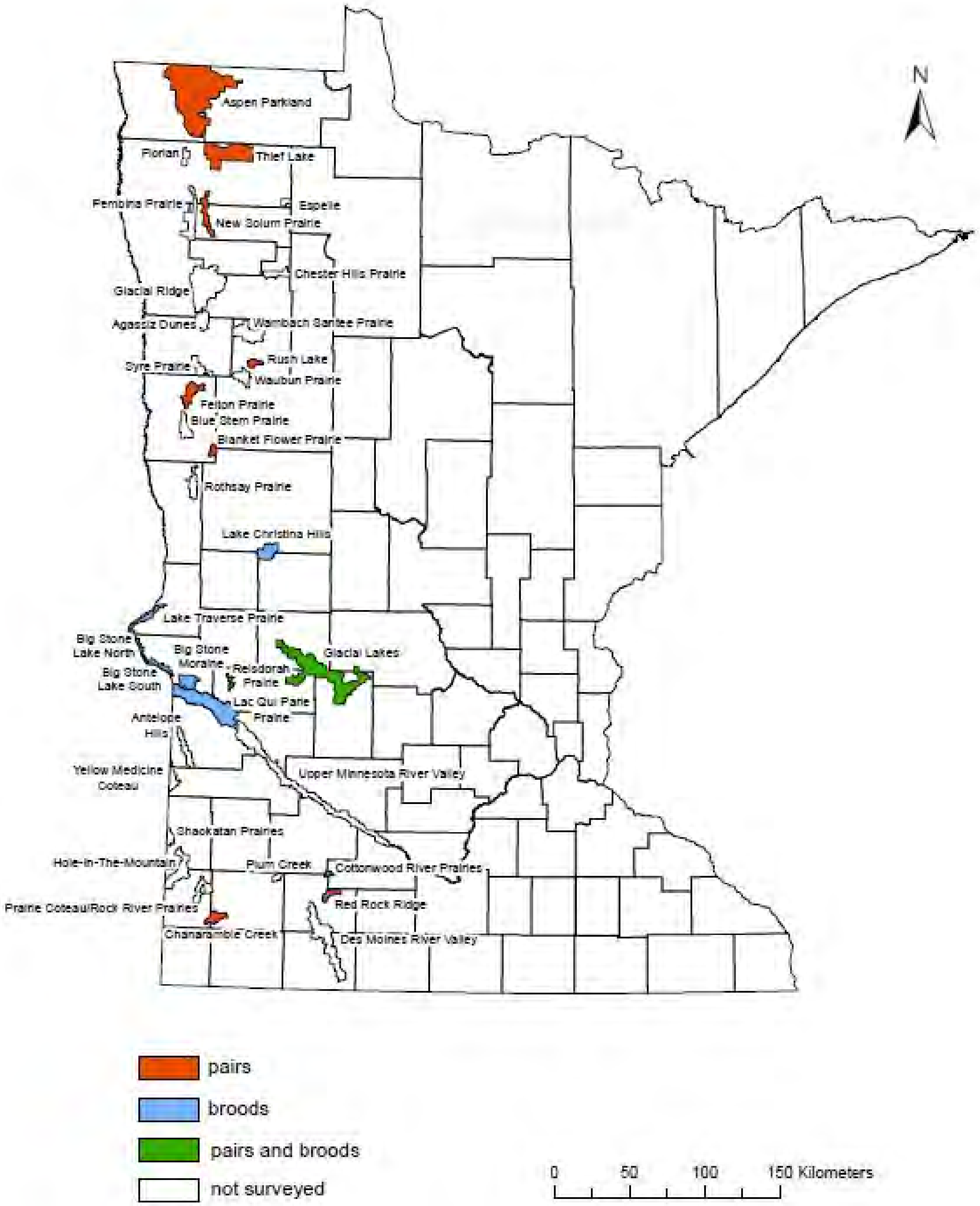

Figure 1. Distribution of core areas (*n* = 36) designated in the Minnesota Prairie Conservation Plan. Observers surveyed nine core areas for pairs, six for broods, and two for both during the 2014 breeding season. Seventeen core areas were not surveyed.

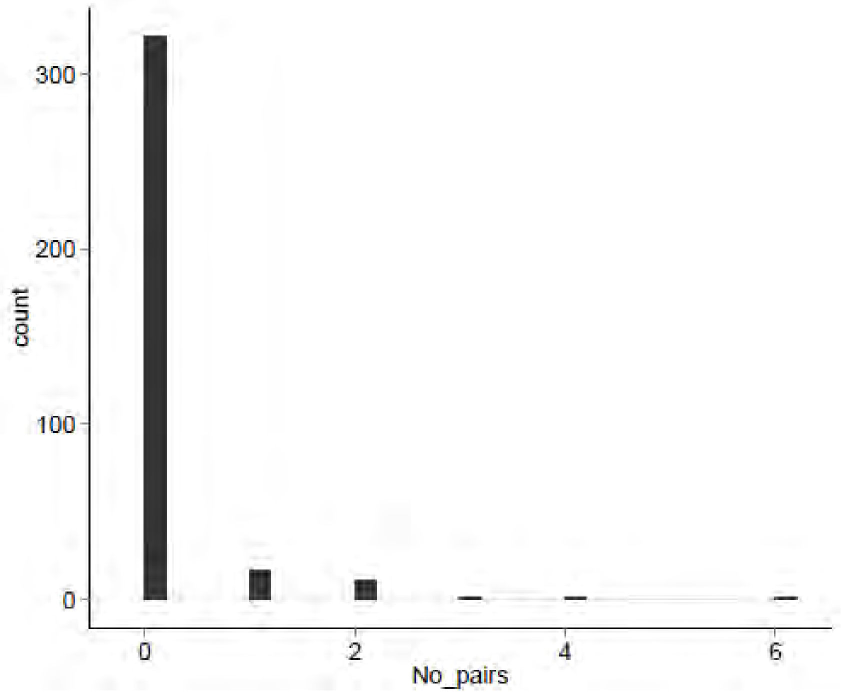

Figure 2. Frequency distribution of the number of indicated breeding pairs (No_pairs) of mallards observed at 352 wetlands within 11 Minnesota Prairie Conservation Plan Core Areas, 2014.

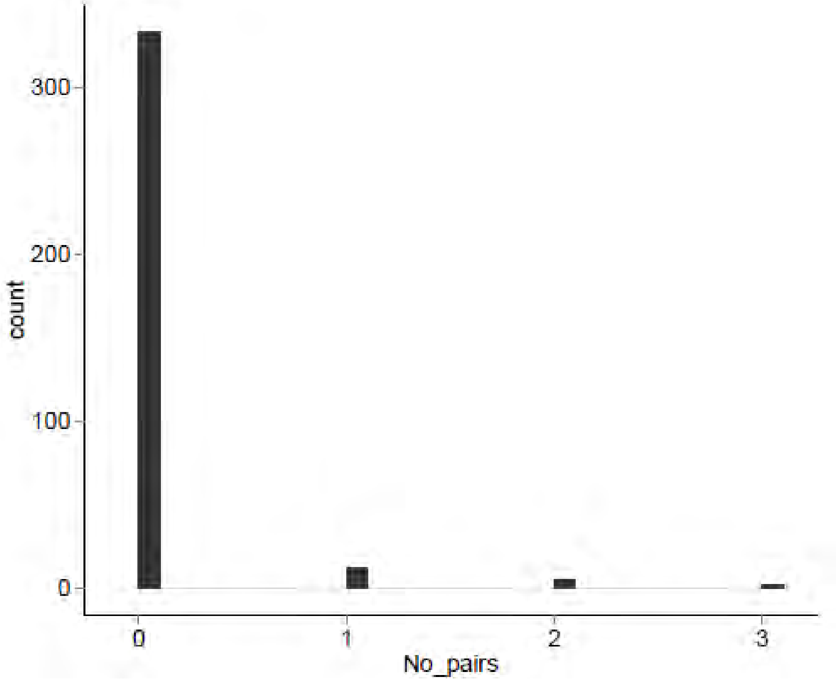

Figure 3. Frequency distribution of the number of indicated breeding pairs (No_pairs) of blue-winged teal observed at 352 wetlands within 11 Minnesota Prairie Conservation Plan Core Areas, 2014.

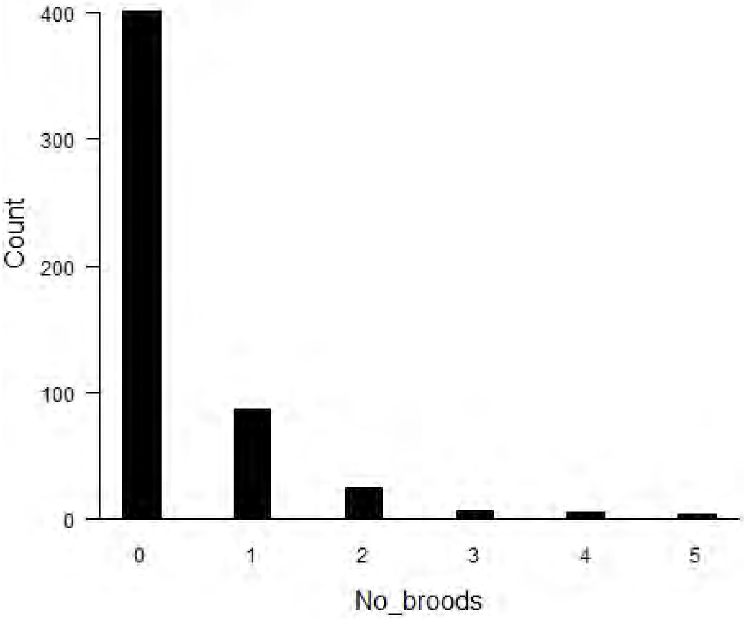

Figure 4. Frequency distribution of broods of all waterfowl species observed during ≥2 visits to 265 wetlands within 4 Minnesota Prairie Conservation Plan Core Areas, 2014.

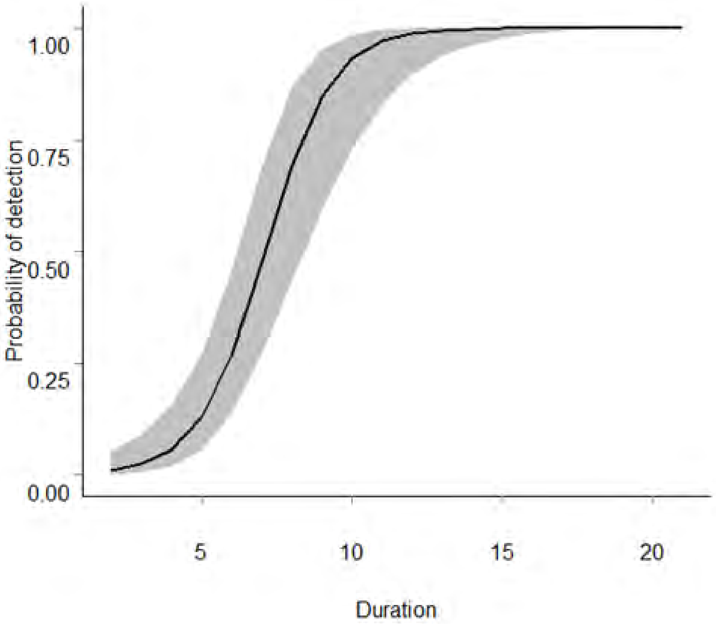

Figure 5. Modeled relationship between the probability of detection of indicated breeding pairs of mallards and survey duration (Duration [min]). Data used in this model were collected at 11 Minnesota Prairie Conservation Plan Core Areas during 2014.

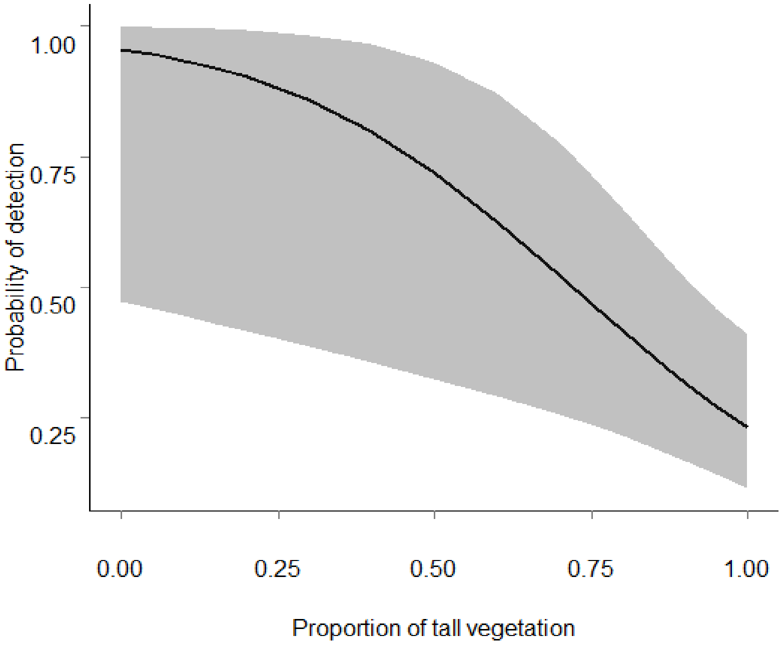

Figure 6. Modeled relationship between the probability of detection of indicated breeding pairs of mallards and the proportions of wetland edges obscured by tall vegetation. Data used in this model were collected at 11 Minnesota Prairie Conservation Plan Core Areas during 2014.

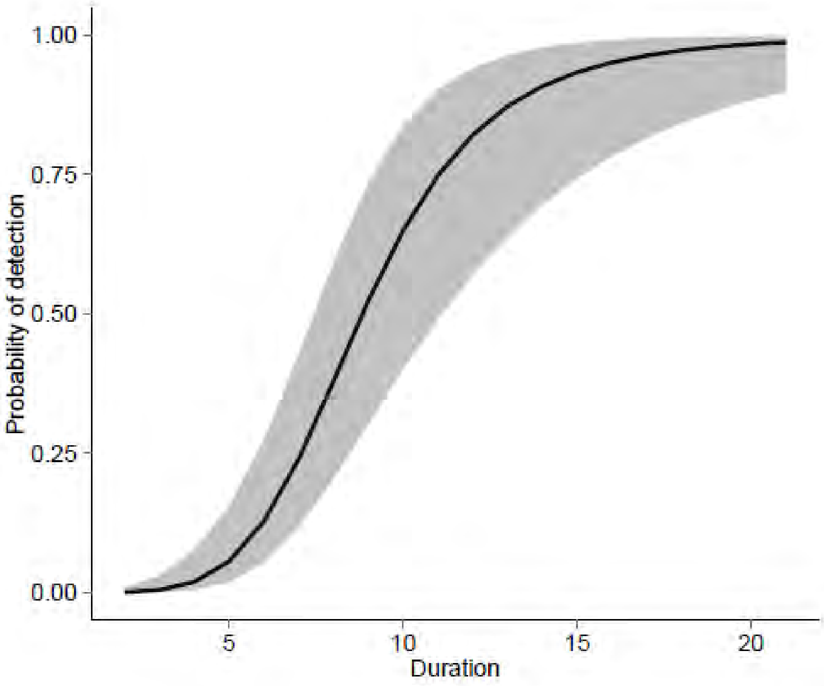

Figure 7. Modeled relationship between the probability of detection of indicated breeding pairs of blue-winged teal and survey duration (Duration [min]). Data used in this model were collected at 11 Minnesota Prairie Conservation Plan Core Areas during 2014.

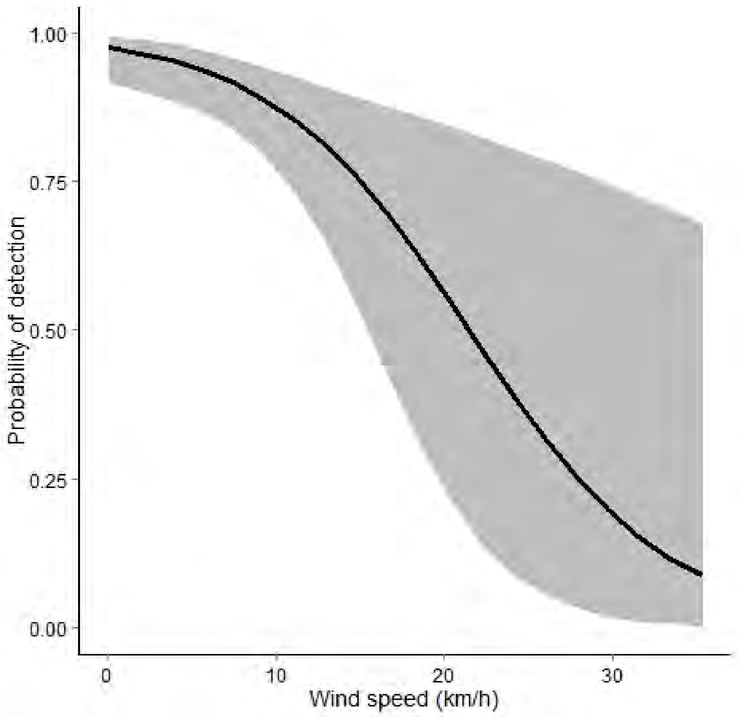

Figure 8. Modeled relationship between the probability of detection of all species of waterfowl broods and *wind speed* (km/h). Data used in this model were collected at 4 Minnesota Prairie Conservation Plan Core Areas during 2014.

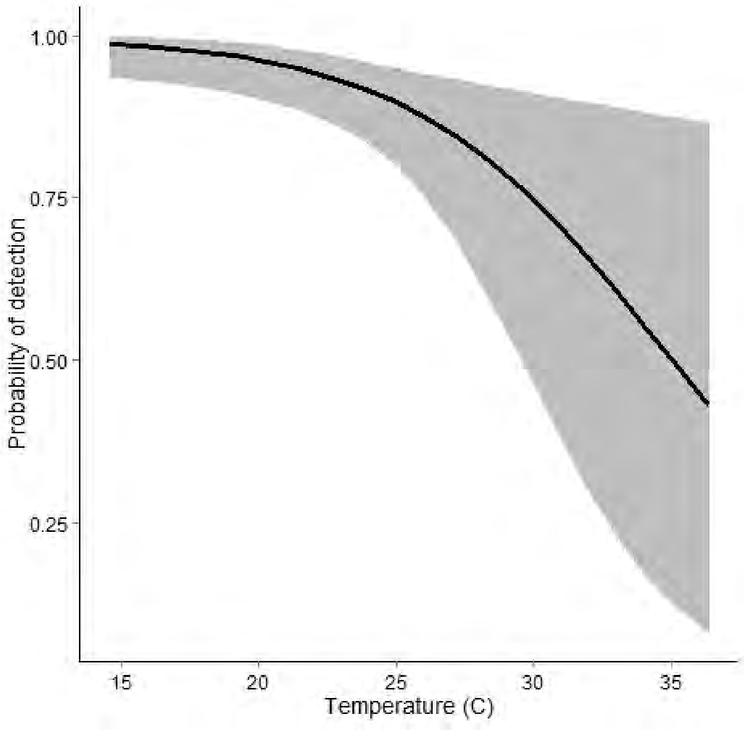

Figure 9. Modeled relationship between the detection probability of all species of waterfowl broods and *ambient temperature* (°C). Data used in this model were collected at 4 Minnesota Prairie Conservation Plan Core Areas during 2014.

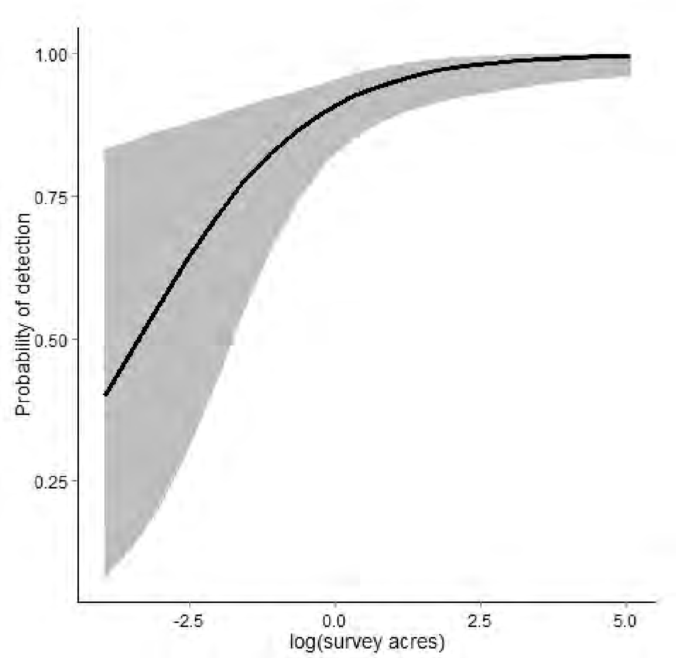

Figure 10. Modeled relationship between the probability of detection for all species of waterfowl broods and log observable area of wetlands (survey acres). Data used in this model were collected at 4 Minnesota Prairie Conservation Plan Core Areas during 2014.

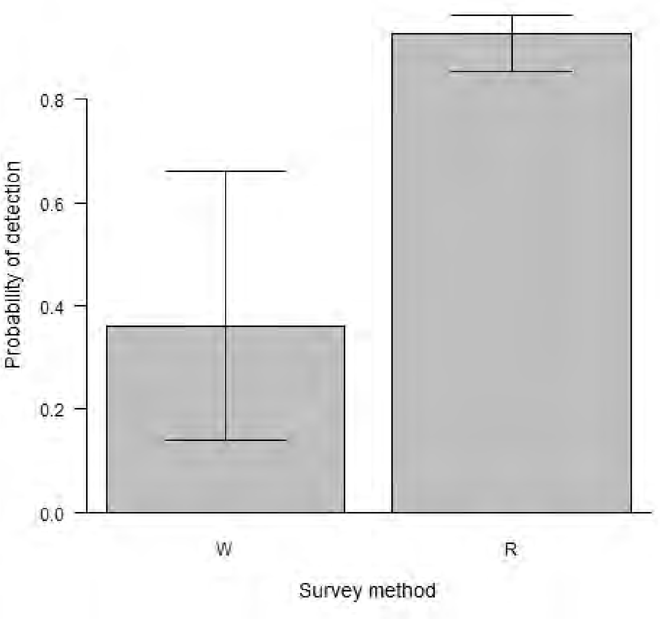

Figure 11. Modeled relationship between the probability of detection for all species of waterfowl broods and 2 survey methods: walk-in (W) and roadside (R). Data used in this model were collected at 4 Minnesota Prairie Conservation Plan Core Areas during 2014. Bars indicate 95% confidence intervals around the coefficient estimates.

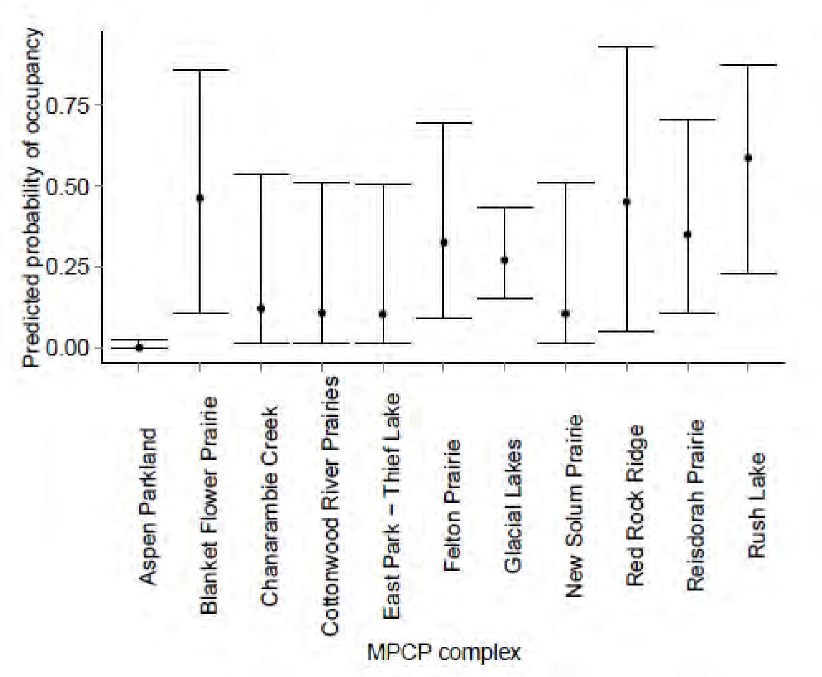

Figure 12. The estimated wetland occupancy of 11 Minnesota Prairie Conservation Plan (MPCP) Core Areas by indicated breeding pairs of mallards, 2014. Bars indicate 95% confidence intervals around the coefficient estimates.

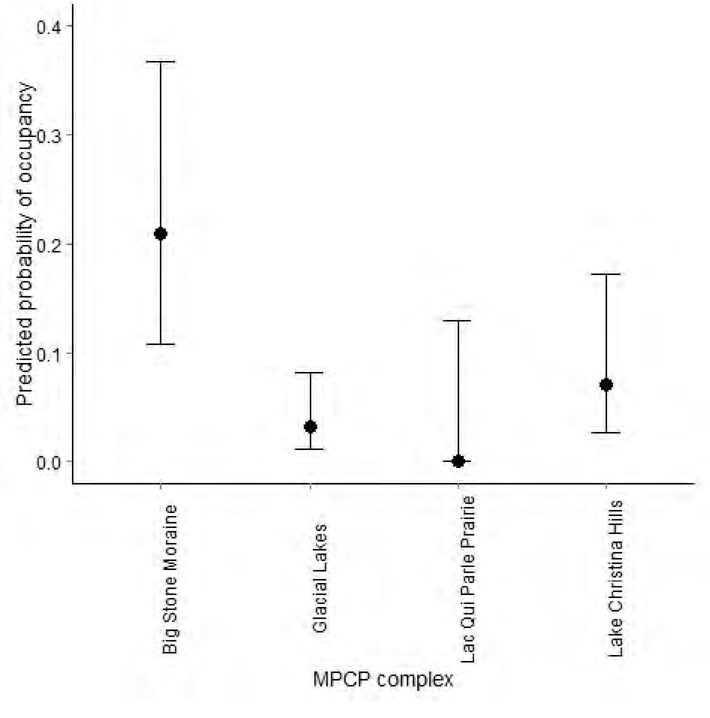

Figure 13. The estimated wetland occupancy within 4 Minnesota Prairie Conservation Plan (MPCP) Core Areas by waterfowl broods, 2014. Bars indicate 95% confidence intervals around the coefficient estimates.

Appendix 1. Results of a 2-stage analysis in which the detection (p) and wetland *occupancy* (Ψ) of breeding pairs of mallards observed at 11 Minnesota Prairie Conservation Plan Core Areas during 2014 were modeled. Approximating models that explain variation in the probabilities of the p of this cohort were developed in the first stage *a*). Models that explain variation in the Ψ of wetlands by this cohort were developed for the second stage *b*), and used the parameterization of p from the top-ranked model of the first stage.

Model [a]	K [b]	AIC	ΔAIC	ω [c]
a) Detection models (occupancy constant)				
$p_{\text{Log SURVDUR + TALLVEG}}$	4	215.8	0	0.58
$p_{\text{Log SURVDUR + Log OAW + TALLVEG + TEMP + Log WIND}}$	7	216.5	0.7	0.42
$p_{\text{Log SURVDUR}}$	3	227.2	11.4	0.01
$p_{\text{Log OAW + TALLVEG}}$	4	242.0	26.2	0
$p_{.}$	2	248.2	32.4	0
$p_{\text{TEMP+ Log WIND}}$	4	249.0	33.2	0
b) Occupancy models (detection varies by Log SURVDUR + TALLVEG)				
Ψ_{CoreA}	14	205.7	0	0.61
$\Psi_{\text{GRASS + DENSWET2-4 + DENSWET5}}$	7	207.4	1.7	0.26
$\Psi_{\text{GRASS + DENSWET2-4 + DENSWET5 + Log OAW + TALLVEG + WETTYPE}}$	14	210.9	5.2	0.05
$\Psi_{\text{Log OAW + TALLVEG + WETTYPE}}$	11	211.0	5.3	0.04
$\Psi_{\text{CoreA + Log OAW + TALLVEG + WETTYPE}}$	17	211.4	5.7	0.04
$\Psi_{.}$	4	215.8	10.1	0

[a] Acronyms of covariates are: SURVDUR = duration of survey, OAW = observable area of wetland, TALLVEG = proportion of wetland edges obscured by tall vegetation, TEMP = temperature, WIND = wind speed, OBS = observer, CoreA = MPCP Core Area, GRASS = proportion of Core Area comprised of grassland, DENSWET2-4 = density of Types II-IV wetlands, DENSWET5 = density of Type V wetlands, WETTYPE = wetland type.

[b] Number of parameters in the model.

[c] Model weights.

Appendix 2. Results of a 2-stage analysis in which the *detection* (p) and wetland *occupancy* (Ψ) of breeding pairs of blue-winged teal observed at 11 Minnesota Prairie Conservation Plan Core Areas during 2014 were modeled. Approximating models that explain variation in the probabilities of the p of this cohort were developed in the first stage *a*). Models that explain variation in the Ψ of wetlands by this cohort were developed for the second stage *b*), and used the parameterization of p from the top-ranked model of the first stage.

Model [a]	K [b]	AIC	ΔAIC	ω [c]
a). Detection models (occupancy constant)				
$p_{\text{Log SURVDUR}}$	3	160.3	0	0.98
$p_{\text{Log SURVDUR + Log OAW + TEMP + Log WIND}}$	7	168.0	7.7	0.02
$p_{.}$	2	180.7	20.4	0
$p_{\text{Log OAW + TALLVEG}}$	4	181.6	21.3	0
$p_{\text{TEMP + Log WIND}}$	4	183.0	22.7	0
b). *Occupancy* models (detection varies by log SURVDUR)				
$\Psi_{\text{GRASS + DENSWET2-4 + DENSWET5 + Log OAW + TALLVEG + WETTYPE}}$	13	150.2	0	0.61
$\Psi_{\text{Log OAW + TALLVEG + WETTYPE}}$	10	151.4	1.2	0.33
$\Psi_{\text{GRASS + DENSWET2-4 + DENSWET5}}$	6	155.0	4.8	0.05
$\Psi_{.}$	3	160.3	10.1	0.00

[a] Acronyms of covariates are: SURVDUR = duration of survey, OAW = observable area of wetland, TALLVEG = proportion of wetland edges obscured by tall vegetation, TEMP = temperature, WIND = wind speed, OBS = observer, CoreA = MPCP Core Area, GRASS = proportion of Core Area comprised of grassland, DENSWET2-4 = density of Types II-IV wetlands, DENSWET5 = density of Type V wetlands, WETTYPE = wetland type.

[b] Number of parameters in the model.

[c] Model weights.

Appendix 3. Results of a 2-stage analysis in which the *detection* (p) and wetland *occupancy* (Ψ) of 3 different species aggregations of waterfowl broods observed at 4 Minnesota Prairie Conservation Plan Core Areas during 2014 were modeled. Approximating models that explain variation in the probabilities of the p of broods of all observed waterfowl species were developed in the first stage *a*). Models that explain variation in the Ψ of wetlands by of broods of all observed waterfowl species were developed for the second stage *b*), and used the parameterization of p from the top-ranked model of the first stage. Models that explain variation in the probabilities of the p of broods of dabbling ducks were developed in the first stage *c*). Models that explain variation in the Ψ of wetlands by of broods of dabbling ducks were developed for the second stage *d*), and used the parameterization of p from the top-ranked model of the first stage. Models that explain variation in the probabilities of the p of broods of cavity-nesting ducks were developed in the first stage *e*). Models that explain variation in the Ψ of wetlands by of broods of cavity-nesting ducks were developed for the second stage *f*), and used the parameterization of p from the top-ranked model of the first stage. Overall *extinction* (ϵ) and *colonization* rates (γ) were estimated in all models.

Species aggregation [a]	Model [b]	K[c]	AIC	ΔAIC	ω [d]
a) All waterfowl	Detection models (occupancy, extinction, and colonization are constant)				
	$p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	9	579.5	0	0.95
	$p_{\text{SURVDUR + Log OAW + TALLVEG + TEMP + WIND + METHOD + START + VISIT}}$	13	586.5	7.0	0.03
	p_{VISIT}	5	588.6	9.1	0.01
	$p_{\text{Log OAW + TEMP + WIND + METHOD}}$	8	590.1	10.6	0
	p_{OBS}	10	590.2	10.7	0
	$p_{\text{Log OAW + TALLVEG}}$	6	595.4	15.9	0
	$p_{.}$	4	597.5	18.0	0
	$p_{\text{TEMP + WIND}}$	6	600.2	20.7	0
	$p_{\text{SURVDUR + START}}$	7	600.3	20.7	0
b)	Occupancy models (extinction and colonization are constant)				
	$\Psi_{\text{WETTYPE}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	11	578.3	0	0.49
	$\Psi_{.}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	9	579.5	1.2	0.27
	$\Psi_{\text{Log OAW + TALLVEG + WETTYPE}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	13	580.3	2.0	0.18
	$\Psi_{\text{GRASS + DENSWET2-4 + DENSWET5}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	12	585.3	7.0	0.02
	$\Psi_{\text{COREA}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	12	585.3	7.0	0.02
	$\Psi_{\text{COREA + Log OAW + TALLVEG + WETTYPE}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	16	585.6	7.3	0.01
	$\Psi_{\text{Log OAW + TALLVEG + WETTYPE + GRASS + DENSWET2-4 + DENSWET5}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	16	585.6	7.3	0.01
	$\Psi_{.}\ p_{.}$	4	597.5	19.2	0
c) Dabbling ducks	Detection models (extinction and colonization are constant)				
	$\Psi_{.}\ p_{.}$	4	242.5	0	0.38
	$\Psi_{.}\ p_{\text{TEMP + WIND}}$	6	243.7	1.2	0.20
	$\Psi_{.}\ p_{\text{VISIT}}$	5	244.1	1.6	0.17
	$\Psi_{.}\ p_{\text{Log OAW + TALLVEG}}$	6	245.0	2.5	0.11
	$\Psi_{.}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	9	246.8	4.3	0.04
	$\Psi_{.}\ p_{\text{SURVDUR + START}}$	7	248.2	5.6	0.02
	$\Psi_{\text{WETTYPE}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	11	249.5	6.9	0.01
	$\Psi_{.}\ p_{\text{SURVDUR + Log OAW + TALLVEG + TEMP + METHOD + START}}$	13	250.3	7.8	0.01
	$\Psi_{\text{Log OAW + TALLVEG.}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	11	250.5	8.0	0.01
	$\Psi_{\text{TALLVEG + WETTYPE}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	12	251.4	8.9	0
	$\Psi_{.}\ p_{\text{OBS}}$	10	252.0	9.5	0

Appendix 3. continued

d)	Occupancy models (extinction and colonization are constant)				
	$\Psi_{\text{GRASS + DENSWET2-4 + DENSWET5}}\ p_{.}$	7	234.2	0	0.46
	$\Psi_{\text{COREA}}\ p_{.}$	7	234.2	0	0.46
	$\Psi_{\text{Log OAW + TALLVEG + WETTYPE + GRASS + DENSWET2-4 + DENSWET5}}\ p_{.}$	11	239.4	5.2	0.03
	$\Psi_{\text{COREA + Log OAW + TALLVEG + WETTYPE}}\ p_{.}$	11	239.4	5.2	0.03
	$\Psi_{.}\ p_{.}$	4	242.5	8.3	0.01
	$\Psi_{\text{JULDATE + WETTYPE}}\ p_{.}$	7	247.1	12.9	0
	$\Psi_{\text{Log OAW + TALLVEG + WETTYPE}}\ p_{.}$	8	249.1	14.9	0
e) Cavity-nesting ducks	Detection models (extinction and colonization are constant)				
	$\Psi_{.}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	9	447.2	0	0.41
	$\Psi_{.}\ p_{\text{TEMP + WIND}}$	6	448.3	1.1	0.24
	$\Psi_{.}\ p_{\text{SURVDUR + Log OAW + TALLVEG + TEMP + WIND + METHOD + START + VISIT}}$	13	449.7	2.5	0.12
	$\Psi_{.}\ p_{.}$	4	450.1	2.9	0.10
	$\Psi_{.}\ p_{\text{Log OAW + TALLVEG}}$	6	450.6	3.4	0.07
	$\Psi_{.}\ p_{\text{VISIT}}$	5	451.3	4.1	0.05
	$\Psi_{.}\ p_{\text{SURVDUR + START}}$	7	455.1	7.8	0.01
	$\Psi_{.}\ p_{\text{OBS}}$	10	455.5	8.2	0.01
f)	Occupancy models (extinction and colonization are constant)				
	$\Psi_{\text{GRASS + DENSWET2-4 + DENSWET5 + Log OAW + TALLVEG}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	14	445.5	0	0.21
	$\Psi_{\text{GRASS + DENSWET2-4 + DENSWET5}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	12	446.1	0.5	0.16
	$\Psi_{\text{COREA}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	12	446.1	0.5	0.16
	$\Psi_{\text{Log OAW + TALLVEG}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	11	446.1	0.5	0.16
	$\Psi_{\text{Log OAW + TALLVEG + WETTYPE + GRASS + DENSWET2-4 + DENSWET5}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	16	448.2	2.6	0.06
	$\Psi_{\text{COREA + Log OAW + TALLVEG + WETTYPE}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	16	448.2	2.6	0.06
	$\Psi_{\text{TALLVEG + WETTYPE}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	12	448.3	2.8	0.05
	$\Psi_{\text{WETTYPE}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	11	448.4	2.8	0.05
	$\Psi_{\text{Log OAW + TALLVEG + WETTYPE}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	13	448.6	3.1	0.05
	$\Psi_{.}\ p_{.}$	4	450.1	4.6	0.02
	$\Psi_{\text{JULDATE + WETTYPE}}\ p_{\text{Log OAW + TEMP + WIND + METHOD + VISIT}}$	12	450.2	4.6	0.02

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[a] Species aggregations are as follows: all waterfowl = mallard, blue-winged teal, American green-winged teal, northern shoveler, gadwall, wood duck, hooded merganser, ring-necked duck, redhead, canvasback, lesser scaup, unidentified scaup, large Canada goose, and trumpeter swan; dabbling ducks = mallard, blue-winged teal, American green-winged teal, northern shoveler, and gadwall; cavity nesters = wood duck and hooded merganser.

[b] Acronyms of covariates are: SURVDUR = duration of survey, OAW = observable area of wetland, TALLVEG = proportion of wetland edges obscured by tall vegetation, TEMP = temperature, WIND = wind speed, OBS = observer, CoreA = MPCP Core Area, JULDATE = Julian date of survey, GRASS = proportion of Core Area comprised of grassland, DENSWET2-4 = density of Types II-IV wetlands, DENSWET5 = density of Type V wetlands, WETTYPE = wetland type.

[c] Number of parameters in the candidate model.

[d] Model weights.

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