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The Abundance and Distribution of Mallards in the Lower Mississippi Alluvial Valley of Arkansas

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Abstract

The management of wintering waterfowl in North America requires flexibility because of constantly changing landscapes and conditions. Many mallards use the lower Mississippi Alluvial Valley (MAV) for wintering habitat, making this an area of emphasis for improving management strategies. In this study, I used mallard observation data from 2009-2014 aerial surveys collected in the Arkansas portion of the lower MAV to explain the abundance and distribution and of mallards. Using spatial hierarchical models and breaking covariate data to 2x2 km grid cells, I analyzed how covariates relate to the changes of abundance and distributions within and among surveys. Mallard abundance and distributions responded positively to surface water along with the land cover habitat inundated by that water. Rice fields, wetlands, soybean fields, and fallow (uncultivated) fields were used most by mallards. My models also showed a strong spatial pattern of mallard abundance across the MAV suggesting that covariates other than the ones used here may be important in better explaining mallard distribution. Biologists in the lower MAV can use these results to better conserve and manage lands for mallards.

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Dedication

To my father.

Table of Contents

Introduction

Understanding the ecological factors influencing the spatial distribution of a species is essential to proper wildlife management and planning (Pressey et al. 2007). The North American Waterfowl Management Plan (NAWMP) was developed to enhance waterfowl populations and habitat (U.S. Fish and Wildlife Service (USFWS) and Canadian Wildlife Service (CWS) 1986). Within this plan, the Joint Ventures (JV) were established to oversee the management and conservation of waterfowl and other migratory birds (USFWS and CWS 1986). The Mississippi Flyway (MF) is one of four major flyways for migratory birds in North America, and is the most heavily used flyway by waterfowl in the United States (Bellrose 1968, Lincoln et al. 1998). Within the flyway, the lower Mississippi Alluvial Valley (MAV) provides essential wetland habitat for overwintering waterfowl (USFWS et al. 2012, Reinecke et al. 1989). The mallard is the most abundant and most harvested waterfowl in North America, and the MAV is known for having high numbers of mallards (*Anas platyrhyncos*) throughout the winter months (Bellrose 1976, Reinecke et al. 1989, Green and Krementz 2008). Therefore, waterfowl managers pay particular attention to mallard populations in developing management and conservation plans (USFWS and CWS 1986; Drilling et al. 2002).

With two temporal scales: a single winter survey, and a single winter season, I used hierarchical Bayesian spatial models to investigate which covariates explained changes in mallard abundance and distribution within the Arkansas MAV. Collecting data in the field is time consuming and costly on a large spatial scale, however remotely sensed data allows information about land cover to be readily assessable and powerful in ecological applications (Kerr and Ostrovsky 2003). I focused on the covariates of land cover, weather, food and surface water availability across the entire MAV. Based on the importance of surface water (Heitmeyer

2006, Reinecke et al. 1989) and known habitat use (Allen 1987, Beatty et al. 2014, Delnecke and Reinecke 1986, Heitmeyer 2006, Reinecke et al. 1989, Reinecke and Loesch 1996, Wright 1956), I developed models to better explain the distribution of mallard abundance in the Arkansas MAV.

Due to changes in availability of resources and weather, the abundance and distribution of non-breeding mallards varies spatially and temporally throughout the winter, therefore understanding what affects within winter movements of mallards will improve waterfowl management (Baldassarre and Bolen 2006, Nichols et al. 1983, Reinecke et al. 1989, Heitmeyer 2006, Hagy et al. 2014). Wintering waterfowl in the MAV often move long distances quickly to find available resources (Beatty et al. 2014, Ji and Jeske 2000). Further, migratory waterfowl use different habitats throughout the year in North America, making coordination amongst JVs and flyways essential for sustainable populations (USFWS et al. 2012). Studies have been done to analyze the relationship of covariates to mallard habitat use, but only at the local or non-continuous scale (Link 2011, Beatty et al. 2014, Hagy and Kaminksi 2015). Hagy and Kaminski (2015) commented that a need exists for waterfowl management to have knowledge of large spatial and temporal habitat availability for waterfowl.

The preferred habitat for waterfowl and the primary foraging habitat for mallards in the MAV consist of flooded agriculture fields, moist-soil wetlands, and bottomland hardwood forests (BHF) (Beatty et al. 2014, Reinecke et al. 1989, Reinecke and Loesch 1996). Seasonal flooding in the MAV has a direct role in the suitability of potential habitat preferred by waterfowl in the MAV (Allen 1987, Heitmeyer 2006, Reinecke et al. 1989). BHF in the MAV historically provided the majority of foraging habitat for mallards (Reinecke et al. 1989). However, since the loss of BHF in the MAV due to the expansion of agriculture, mallards altered their diet during the winter to include seeds from moist-soil plants, acorns (*Quercus sp.*), aquatic vegetation, and adding agriculture foods such as rice (*Oryza sp.*), soybean (*Glycine sp.*) and corn (*Zea sp.*) (Delnecke and Reinecke 1986, Drilling et al. 2002; Allen 1987, Heitmeyer 1985), so it is imperative that important areas for current waterfowl use in the MAV are managed and conserved properly (Murdoch et al. 2000, Reinecke et al. 1989, Walther et al. 2002).

I expected that as the preferred habitat of mallards in the Arkansas MAV became flooded, an increased abundance of mallards would occur and show why the distribution across the landscape is dynamic. These findings should improve the understanding of wintering waterfowl in the MAV, and should allow the JVs, land managers, and private stakeholders to make more informed decisions in planning and executing conservation plans within the Arkansas MAV, lower MAV and MF.

Methods

Study Area

The MAV is the floodplain for the Mississippi River (Reincecke et al.1989) covering 10 million ha, of which Arkansas encompasses 3.7 million ha. Topography is flat in the region, rarely exceeding 10 m (Reinecke et al.1989), and so the MAV is subject to winter flooding from winter precipitation and overflowing tributaries. However, hydrology in the MAV has been severely altered due to agriculture and damming of rivers. Bottomland hardwood forests were once abundant in the MAV, but agricultural development and flood control has substantially decreased total area of forests available for wildlife (Forsythe and Gard 1980, Reinecke et al. 1986, Stewart et al. 1988). Reforestation efforts have taken place, but these efforts alone have not restored the forests to their historical range or function yet (King and Keeland 1999). The land covers thought to be most important for mallards in the MAV, and which I used for my models, proportionally covered the MAV in the following percentages from the winter seasons of 2009-2014: soybean fields (31-34%), wetlands (BHF and herbaceous wetlands) (19%), rice fields (10-17%), corn fields (3-8%), fallow (uncultivated) fields (4-6%), and permanent water (5-7%) (USDA-NASS 2009-13). Crowley's Ridge lies within the region, but I did not include this area in my study (Figure 1).

Survey Design

The Arkansas Game and Fish Commission (AGFC) conduct annual winter aerial surveys in the Arkansas MAV. I used data collected from 19 AGFC winter waterfowl surveys from 2009-2014. Four surveys were done each winter season in November, December, early-January and late-January. The January 2014 survey was not done due to lack of funding, totaling 19 surveys for my analyses.

During the 2009-10 and 2010-11 winter season, the MAV was divided into five strata based on expert opinion (Reinecke et al. 1992) and the major rivers in the region (L.W. Naylor, AGFC, pers. comm.). In the 2011-12 season, a stratified random design was implemented, dividing the MAV into eleven strata based on unit-level watershed boundaries (U.S. Geological Survey hydrologic unit code 8) (Seaber et al. 1987) in the region (S. Lehnen, USFWS, unpublished data) and were used for the remainder of the study. I did not include strata as a variable in my analyses, so the change in strata during the study is not an issue. Transects were randomly chosen within the strata. Surveyors recorded the date, number of individual mallards detected and UTM coordinates of observations (L.W. Naylor, AGFC, pers. comm.). Total length of combined transects for all surveys ranged from 3,700-5,600 km, which sampled ~20% of cells (see below) in the analysis.

Covariates

I chose 13 covariates that were previously found to affect mallard habitat use in the winter months (Table 1). I used six land cover covariates: rice fields (*Oryza sp.*), soybean fields (*Glycine sp.*), corn fields (*Zea sp.*), wetlands (bottomland hardwood forests and herbaceous emergent wetlands) and permanent water (Allen 1987, Beatty et al. 2014, Nichols et al. 1983, Drilling 2002, Reinecke et al. 1989, Heitmeyer 1985). I also found that mallards were using fallow fields during the study by looking at where raw counts of mallards occurred on the landscape, and included this habitat type as a sixth land cover covariate. I obtained all land cover covariates, except surface water (see below) from the Cropland Data Layer (CDL) (USDA-NASS 2009-2013). The CDL is a publicly available raster data set that annually updates land cover of agriculture fields and other land covers throughout the continental United States. The spatial resolution for the data I used was 56 x 56 m (2009) and 30 x 30m (2010-2013) (USDA 2009-2013). Surface water affects waterfowl distribution in the winter (Reinecke et al.1989, Heitmeyer 2006), so I predicted that the abundance and distribution of mallards would be positively related to surface water. I used geoprocessing techniques (see below) to access historical surface water at the time of surveys for a covariate.

Residual crops that remain in a field post-harvest (waste crop) can used as a food source for waterfowl, and can positively influence mallard habitat choices (Kross et al. 2007, 2008, Stafford et al. 2005, 2006, 2010, Havens et al. 2009). However, data for relative amounts of waste crop per ha were not available for the MAV. To gauge the amount of waste crop available to mallards, I used the annual harvest yield at the county level for rice, soybean, and corn. Harvest yields were obtained from the United States Department of Agriculture (USDA) annual crop data (USDA-NASS 2014). I assumed a higher crop yield at the county level related in a positive linear manner to a higher potential waste crop. Corn, rice, and soybean degrade at different rates throughout the winter (Nelms and Twedt 1996). I used the crop yield value (USDA-NASS 2014) for the waste crop value in November surveys. I calculated waste crop for each survey thereafter by the degradation values outlined in Nelms and Twedt (1996). When grid cells (see below) overlapped two or more counties, the calculated yield was averaged for that cell.

The severity of weather can affect winter mallard movement and habitat selection (Schumner et al. 2010). I included Schumner's winter severity index (WSI) in the year models to see how WSI related to mallard abundance and distributions. S. Lehnen (USFWS, unpublished data) found a higher number of mallards occurred in the Arkansas MAV with increased severe winter weather in Missouri. I obtained weather data from the United States Historical Climatology Network (Menne et al. 2015) at 9 weather stations around the Arkansas MAV (Figure 2), and calculated the WSI values based on the methods of Schumner et al. (2010) for each survey day at the 9 weather stations. I averaged individual survey day WSI values among multiple survey days, and interpolated the averaged values among the weather stations, creating a smooth gradient of WSI values across the MAV.

I included federal and state managed lands to evaluate if mallard distributions related to public managed lands, and combined national wildlife refuges (NWR), wildlife management areas (WMA), and waterfowl management units (WMU) into a single covariate (managed land). I used reclaimed wetlands from the Environmental Quality Incentives Program (EQIP) as a separate covariate to assess the potential effectiveness of the EQIP program.

Geoprocessing

Esri ArcGIS (ESRI 2014) was used for all Geographic Information System (GIS) analyses. I created Esri shapefiles for all covariates and the mallard observations. All data layers

(CDL, managed lands, Landsat imagery) extending outside the limits of the Arkansas MAV were deleted, leaving only data within the Arkansas MAV.

Landsat (Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), Operational Land Imager (OLI)) imagery (Path/Row, 23/35, 23/36, 23/37, 24/35, 24/36, 24/37) was used to obtain the flooded surface water at the time of each survey (USGS 2009-2014)(Table 2). Due to the temporal spacing of Landsat imagery and unusable images due to cloud cover, dates of images vary between survey date and +/- 14 days of a survey. Landsat 7 ETM+ has a well-known error when the scan line corrector malfunctioned (SLC-Off), causing diagonal lines of missing data across an image (Markham 2004). Due to the difficulty in classifying Landsat 7 ETM+ SLC-Off images (Markham 2004) and having many images with the SLC-Off error (43/126), I processed each image individually by conducting an unsupervised classification.

The Normalized Water Diversity Index (NDWI) was used to delineate surface water in Landsat imagery (McFeeters 1996). Delineating water from Landsat imagery can be accomplished in multiple ways (Rokni et al. 2014). I used NDWI calculated with the green and near infrared (NIR) Landsat bands (green + NIR/ green – NIR) (McFeeters 1996). I found this method to visually have fewer errors with the Landsat images for this study.

To identify any misidentification of water, I visually compared the NDWI to the Landsat NIR of the same scene. Water will absorb the NIR band, causing water to be darker in the image (McFeeters 1996), and I removed any misidentifications determined not to represent water in the NDWI layer. To remove permanent standing water from the classification leaving just flooded surface water, I obtained Landsat images from the summer months (July-September) corresponding with lowest amount of rainfall (Menne et al. 2015). Going through the above process, I identified and deleted the permanent water from the NDWI layer, leaving only the surface water at the time of each survey.

Statistical Analysis

I completed all statistical analyses with R version 10.3 (R Core Team 2015). I used Markov chain Monte Carlo (MCMC) model fitting within the Bayesian framework to explain mallard abundance and distributions in the MAV (Chakraborty et al. 2010). All models had a response of mallard abundance corrected for a combination of covariates (Table 3). I developed an agriculture model to assess whether agriculture land in the form of rice, soy, corn and fallow fields along with waste crop explained mallard abundance. Land cover interactions with surface water models were developed by using land cover types explained to be important to mallards in previous studies and I added surface water as an interaction term or as a main effect. Finally, I modeled to see if water alone (surface water, permanent water) best explained mallard decisions with no other covariates. I added WSI to the land cover models only in the within-year models to see how weather affected mallards over time. Surface water changed as the winter season progressed, changing the availability of potential habitat for mallards. Instead of running the model for a single survey (see above), I combined all surveys within a year and ran the competing models. Combing surveys allowed to test for covariate importance throughout the year, and increased the temporal scale of the model. Additionally, I included a lag time component covariate to within-year models to see if conditions in the previous month influenced mallard abundance and distribution during the following month. The November surveys were the first step in the MCMC process, so November surveys did not have parameter estimate for time.

I modeled at the grid cell level (Chakraborty et al. 2010) by dividing the MAV into grid cells of equal size (2 x 2 km), totaling approximately 10,500 4 km^2 cells. I used a 2 km grid to limit the number of grid cells, which reduced processing time in the MCMC. Additionally Beatty et al. (2014) found that local movements of radio-marked mallards ranged from a distance of 0.25 to 30 km. I used a 2 x 2 km grid cell to have a fine resolution for spatial scale, stay analyze local movements as stated in Beatty et al. (2014), and to not impact the processing time of analysis. Dependent on the percentage of land cover, I assigned each cell covariate values ranging from 0 – 1.0. Correlation among covariates was tested and I excluded any covariate with a linear dependence with the calculation (Variance Inflation Factor (VIF) = $1/(1-r^2)$). I excluded any covariate with a VIF $> \sim 4$, in order to exclude any covariate with an r^2 value of ~0.75. I ran each model with a MCMC chain length of 20,000, a burn-in length of 5,000 and thinned at every fourth sample. All models had a prior distribution with a mean = 0 and deviance = 2.5.

I placed mallard abundance per cell into four categories to reduce processing time, improve the model fitting (A. Chakraborty, Univ. Arkansas, pers. comm.). Detectability of mallard observations varied among habitat types, especially in closed canopy habitat (Smith et al. 1995). Using a categorical response value reduced the potential sampling bias in the aerial surveys (Chakraborty et al. 2010). The four groups were: 1) Group 0 - no observed mallards, 2) Group 1 - 1-15 mallards, 3) Group 2 -16-100 mallards, and 4) Group 3 - 100 + mallards. Categories were determined by examining the quantile breaks of cell observations for each survey and by observing waterfowl groups in the field (L.W. Naylor, AGFC, pers. comm.).

I compared models using the Deviance Information Criterion (DIC) (Spiegelhalter et al. 2002). Based on the top model selected by DIC score, I examined the posterior β estimates, potential abundance and distribution, and the posterior mean of spatial effects. When the 95% confidence interval of a covariate's β estimate s did not overlap zero, I considered that covariate associated with mallard abundance. I examined the relative importance of covariates within the top models by looking at the median/interquartile range (IQR) and mean/standard deviation.

To account for spatial patterns from factors not represented by the covariates and how mallard abundance may be associated with the neighboring cells, I added a spatial random effect (θ) to each model (Chakraborty et al. 2010, Gelfand et al. 2006, Ver Hoef et al. 2001). Using θ in the model strengthens the predictive capability and interpretation of the model results. Additionally, θ allows for an explanation of the effect of covariates in cells that are not sampled (Gelfand et al. 2006). To visualize the spatial random effect (θ), a smoothed surface output of expected mallard abundance is applied to the MAV, showing the posterior mean of spatial effects (θ) by grid cells. If no spatial effect occurred, the maps of θ would show no patterns and the values of θ would be random throughout the MAV. Cells with a value greater than zero represent areas with a larger than expected abundance suggesting the covariates over-predicted mallard abundance, and cells with a value lower than zero represent areas with a lower than expected abundance suggesting the covariates under-predicted mallard abundance. As in Chakraborty et al. (2010) I used a binary matrix with a threshold of 0.036 for θ to allow for approximately 9 nearest neighbor cells. A conditional auto-regressive model was used for θ and was fitted into the model just as the other parameters.

Additionally, as in Chakraborty et al. (2010), I predicted the likelihood of the mallard abundance categories to occur within a cell. The probability of mallards to occur within a cell was estimated in relation to the covariates, and then predicted the distribution of mallard abundance to occur within the MAV. These maps are useful in observing the change of mallard distributions across the MAV and can be related to the covariates to see why the distributions of mallards are changing.

Results

Single-survey Models

I ran all models separately for each waterfowl survey from November 2009-January 2014 (n=19). Across all models tested, I found that the global (n=7) and land cover + surface water (n=12) were the only models that ranked as top model based on DIC (Table 4). The December and early-January surveys were the only surveys to have the global model perform best by DIC. Land cover + surface water was a top model by DIC in all four surveys, but it occurred most in the November and late-January surveys (Table 4).

Surface water was consistently positively associated with mallard abundance. As a main effect, surface water had a positive association with mallard abundance (n=4) and as an interaction with land cover covariates (n=21). Rice fields, wetlands, fallow fields, soy fields and permanent water all had parameter (β) estimates positively associated with mallard abundance. Comparing beta estimates by importance (mean/standard deviation), surface water was the most important covariate positively associated with mallard abundance in 11 out of 19 months (see supplemental data). Corn fields, EQIP land, and managed land did not influence mallard abundance.

The posterior mean of spatial effects (θ) and predicted likelihood for the distribution of mallard categorical abundance were similar to the within-year models (see supplemental data). The maps of θ showed a spatial relationship for every survey. The θ maps consistently had a trend throughout the study occurred in that northern latitudes in every November survey had positive θ values and negative θ values in the southern latitudes. In the late-January survey, the relationship was the opposite with negative θ values in the northern latitudes and positive θ values in the southern latitudes. Only the late-January 2012 survey did not show this trend, and the majority of the MAV had positive θ. Coincident with the patterns in theta over time within a year was the change in the predicted likelihood abundance maps within a year (see supplemental data). In all November surveys, predicted mallard abundance was greater in the northern latitudes of the MAV. In all late-January surveys, predicted mallard abundance was greater in the southern latitudes of the MAV. Additionally, surface water, and surface water interactions with soy fields and wetlands had the most important posterior parameter estimates in 12 surveys (see supplemental data), and suggests areas with mallard abundance in categories 1-3 were associated with the presence of surface water. In 11 months, the posterior mean of spatial effects (θ) cells in the mid-latitudes of the MAV had θ values close to zero, and suggested the covariates explain mallard abundance well in those areas.

Within-year Models

Model performance within-year was similar to the within-month models. The land cover + surface water model and the global model were again the best performing models. Land cover + surface water was the top performing model in the 2009-10, 2010-11, and 2012-13 winter seasons. The global model was the top-performing model in the 2011-12 and 2013-14 winter seasons (Table 5).

Surface water was consistently positively associated with mallard abundance. As a main effect, surface water had a positive association with mallard abundance (n=5) and as an interaction with land cover covariates (n=20). Rice fields, wetlands, fallow fields, soy fields and permanent water all had beta estimates positively associated with mallard abundance. WSI had beta estimates negatively associated with mallard abundance in 13 months (Table 8). Comparing beta estimates by importance (mean/standard deviation), surface water was the most important covariate positively associated with mallard abundance in 11 out of 19 months. WSI ranked highest among covariates in 6 out of 19 months. The time component was positively associated with mallard abundance in 12 out of 14 possible months. (Table 7).

As in the within-month top models, all November surveys had positive θ values in the northern latitudes and negative θ values in the southern latitudes, and a reverse relationship in all late-January models, with exception of the 2012 late-January survey (Figures 7-10, supplemental data). In 11 months, the posterior mean of spatial effects (θ) cells in the mid-latitudes of the MAV had θ values close to zero, and suggested the covariates explain mallard abundance well in the mid-latitudes. The most important posterior parameter estimates for the months with θ values close to zero in the mid-latitudes were surface water, WSI, soy*surface water, and wetlands. Again, coincident with the patterns in theta over time within a year was the change in the predicted likelihood abundance maps within a year (Figures 3-6, supplemental data). Additionally, surface water had the most important posterior parameter estimates in 10 surveys (see supplemental data), and suggests areas with mallard abundance in categories 1-3 were associated with the presence of surface water.

During most surveys, WSI averaged a negative value across the MAV, meaning the temperature in the MAV was above freezing with low amounts of snow cover. WSI was negatively associated with mallard abundance in the MAV during the survey, which suggests that mallards were located in areas with warmer and dryer conditions.

Discussion

Winter flooding in the MAV increases foraging opportunities for mallards, causing the redistribution of mallard abundance (Heitmeyer 2006, Reinecke et al.1989). I found that surface water was the most important covariate for mallard abundance and distribution. I also found that surface water alone cannot explain habitat use, but requires land cover that has the ability to provide additional resources needed (i.e. food and cover). Models without both land cover and surface water covariates never performed as top model in any survey. Although not novel information that mallards are using land with surface water (Heitmeyer 2006), applying mallard habitat use in relation to surface water availability over a large landscape provides needed information to waterfowl winter ecology (Hagy and Kaminski 2015).

Wetlands, rice fields, and soybean fields are a preferred habitat for mallards in the MAV and provide adequate food resources during the winter months (Allen 1987, Dabbert 1991, 2000, Heitmeyer 2006, Wright 1956). Recent ecological models have not included surface water as a covariate (Beatty et al. 2014, Krementz et al. 2012). Beatty et al. (2014) found tagged individual female mallards in the MAV use agriculture fields, wetlands and open water, as well as other studies using tagged individual mallards to investigate habitat use (Davis et al. 2011, Krementz et al. 2012). The absence of surface water availability in habitat use models of individually tagged mallards leave gaps in waterfowl winter ecology. My results demonstrate that surface water needs to be included when modeling the habitat use of mallards.

As historical surface water data becomes available (J. Jones, USGS, pers. comm), waterfowl ecologists can return to historical waterfowl data for comparison with minimal processing time of remotely sensed data. Pernollet et al. (2015) used satellite imagery to find timing of flooded rice fields in relation to habitat suitability for mallards. Additionally, the LMVJV has used satellite imagery to investigate historical flooding in the MAV (Edwards et al. 2012). The LMVJV has also continued to research extracting water from satellite imagery (M.Mitchell, USFWS, pers. comm.). I showed that flooded wetlands are important habitats for mallards, which support current management suggestions in the literature (Foth et al. 2014, Kross et al. 2007, 2008, Leach et al. 2012) to properly manage the timing of flooding wetlands.

I found mallard abundances distribute to flooded rice fields in the MAV. Rice is known to be an important food source for mallards in the MAV and provides valuable nutrients needed in the winter (Allen 1987, Drilling et al. 2002, Loesch and Kaminski 1989). Rice was not the most abundant crop in the MAV, covering 10-17% of the land cover during the years of the study. Current rice field management practices have been a concern for the availability of waste rice to waterfowl (Stafford et al. 2005, 2006, 2010). My measure of waste crop did not explain mallard abundance well, however some measure of waste crop should be used in habitat use models. My results support the need for managers to monitor and work with the rice industry to improve land management on rice fields (Kross et al. 2007, Manley et al. 2005, Stafford et al. 2010). Similar to rice, corn provides mallards with nutrients and is an important part of mallard winter diet (Allen 1987). However, I did not find corn to be positively associated with mallard abundance. Corn was not widespread in the MAV during this study, covering only 3-8% of the total land cover. The difference between rice and corn being positively associated with mallard abundance was possibly due to habitat availability, or availability from surface water flooding rice fields more frequently.

Mallards can choose a certain habitat for reasons other than food availability (Hagy and Kaminski 2015). I found soybean fields to have a greater than expected influence on mallard abundance, which is counterintuitive because soybeans provide fewer nutrients than rice and corn (Allen 1987), and degrade faster than rice and corn (Nelms and Twedt 1996). Because soybean fields represented a third of the total land cover in the MAV I hypothesize that mallards may use soybean fields in accordance to availability (Heitmeyer 1985). Fallow fields also influenced mallard abundance more than I expected considering that fallow fields only represented 4-6% of the total land cover in the MAV. Other variables such as weed growth or invertebrates not included in the models may also explain the strong association soybean and fallow fields had with mallard abundance.

I used diurnal observations for the study, and flocking of high numbers of mallards occurred frequently at crepuscular periods (pers. observation). Mallards may possibly be using habitat that does not provide as much food such as soybean and fallow fields as diurnal sanctuaries to avoid hunting pressure. Sanctuaries may be vital for mallard abundance in the MAV and are used daily in the MAV (St. James et al. 2013). Hunting pressure can cause mallard distributions to disperse away from hunters (Dooley et al. 2010). The difficulty of having a reliable measure of hunting pressure is why I did not include hunting pressure in the models. If soybean and fallow fields are being used as sanctuaries, further research is warranted to explain mallard abundance on soybean and fallow fields.

Managed and EQIP land did not explain mallard abundance as much as I would have been expected. However, I believe that managed land and EQIP are important variables for mallard abundance. I observed high numbers of mallards in close proximity to managed lands even though managed land covered only 5% of the total MAV. I suspect that the low amount of managed land cover may be a reason that managed land was not related to mallard distributions.

Weather conditions can affect the movement and location of mallards during winter in the MAV (Schumner et al. 2010, Nichols et al. 1983). Mallards make regional movements depending on the regional weather conditions and tend to be less abundant in the MAV under warmer and drier conditions and increase in abundance when conditions are colder and wetter (Nichols et al. 1983, Schumner et al.2010). Too, S. Lehnen (USFWS, unpublished data) saw an increase of mallards in the Arkansas portion of the MAV with higher WSI values in northern latitudes of mid-Missouri. My results demonstrated the same patterns with one important difference being that I was just examining movements only within the MAV.

The posterior mean of spatial effects (θ) demonstrated a spatial relationship occurred in the Arkansas MAV to mallard abundance. The trend of θ values latitudinal flipping in the MAV from November to late-January may suggest mallards moving to southern latitudes as the non-breeding season progresses, and the top model is not fully explaining why that occurs. This may suggest that I did not include all important variables in my candidate models (Chakraborty et al. 2010, Gelfand et al. 2006). Two examples of variables that might further explain spatial mallard patterns over time are hunting pressure and surface water depth. Another reason why the current covariates did not explain spatial patterns well was that the current modeling approach only includes linear patterns between covariates and mallard abundances and distributions. It may very well be the case that the covariates relate to mallard abundances and distributions in a non-linear relationship (A. Chakraborty, Univ. Arkansas, pers. comm.).

Information concerning the spatial patterns of mallard abundance over time is necessary to develop management plans and my research should help in addressing issues such as habitat connectivity (Twedt and Loesch 1999). Spatial patterns are important for conservation at different scales (Pressey et al. 2007), and my research has improved our understanding of spatial relationships for mallards at a large spatial scale (Hagy and Kaminski 2015).

Management Implications

Managers can use my results to make more informed decisions when managing for waterfowl in the MAV. I showed that soybean fields, rice fields and wetlands are important habitat for mallards in the MAV. Land in the MAV managed by state or federal agencies only covers ~5% of the total land in the MAV, meaning that a lot of waterfowl habitat is private land.

This research can be used to show private land owners the important role their land has to waterfowl over a large spatial scale.

I found that availability of surface water can influence mallard abundance on a large spatial scale, and high abundance of mallards can be expected from covariates in the MAV and contribute to research needed for wetland landscape ecology (Haig et al. 1998). Surface water conditions will also be affected by a changing climate (Murdoch et al. 2000). Future conditions in the ecosystem due to changing climates need to be assessed at all levels (Walther et al. 2002, Murdoch et al. 2000) so managers can use the research in this study to assess management plans at the scale of the Arkansas MAV.

Most states conduct yearly waterfowl surveys, which are used to conduct population estimates and establish hunting regulations. Those surveys can also be used to see what is attracting waterfowl to certain locations and improve waterfowl management. The remotely sensed data used for this study was obtained free of cost, which makes this type of analysis easily translatable across states and flyways. This study also shows that we can look at historical waterfowl data and determine the temporal history of waterfowl ecology, at a relatively low cost to the researcher.

If state and federal wildlife agencies adopt a similar survey design to the AGFC, the continuity of survey design can be an effective tool for managing waterfowl in North America and reach the goals of NAWMP. Spatial data has been collected for many years for different species, such as the Christmas Bird Count. Attempts should be made to expand these techniques to other species of waterfowl, as well as other wildlife species.

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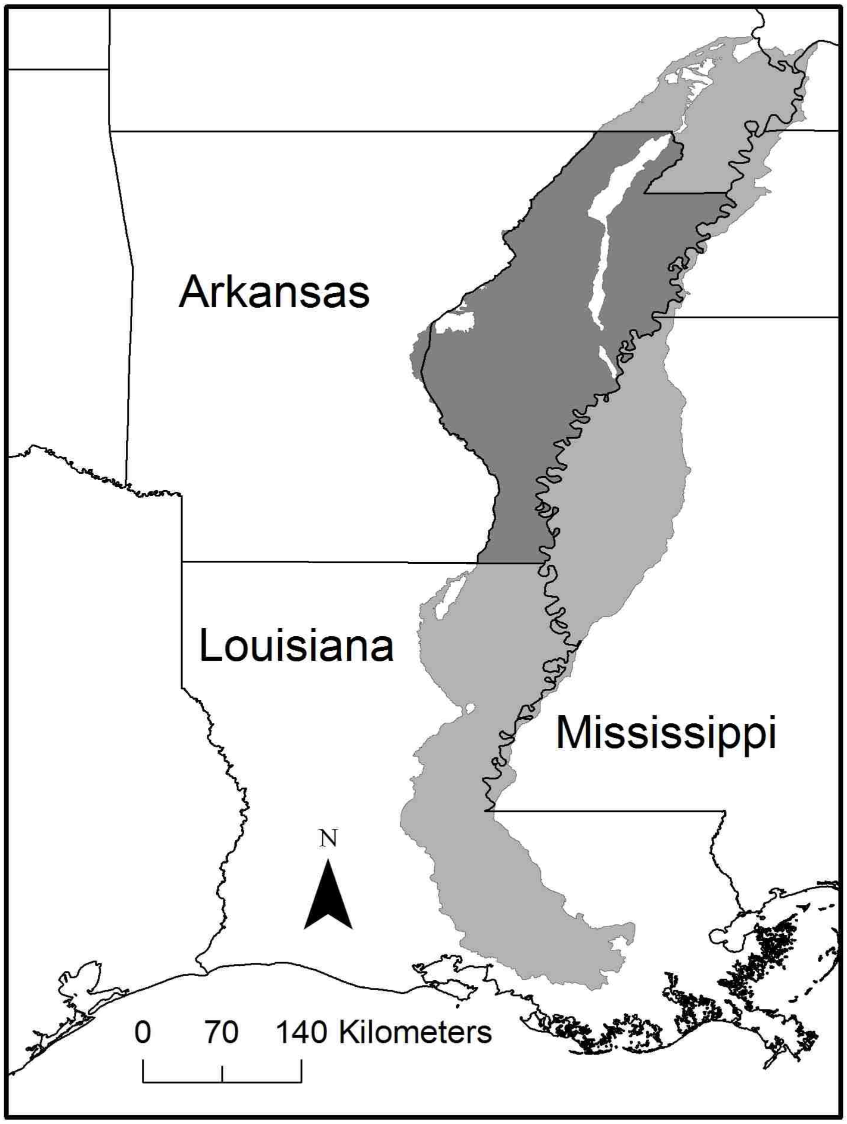

Figure 1. Mississippi Alluvial Valley (MAV) highlighted in gray. Dark gray highlights Arkansas portion of the MAV. White region within the Arkansas MAV represents Crowley's Ridge, which was not included in the study (Credit: S. Lehnen unpublished data).

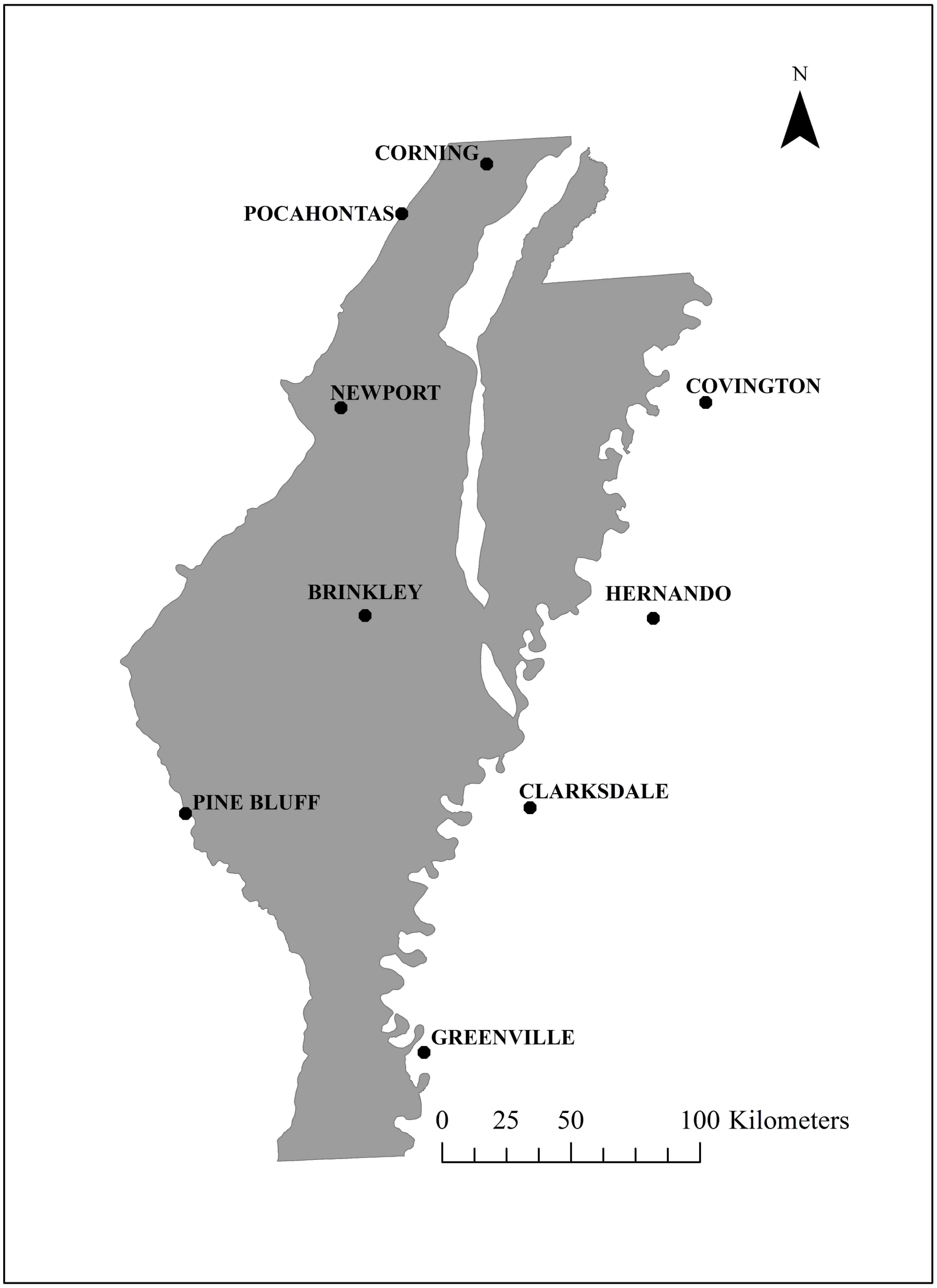

Figure 2. Location and names of weather stations used for weather severity index (Schumner et al. 2010).

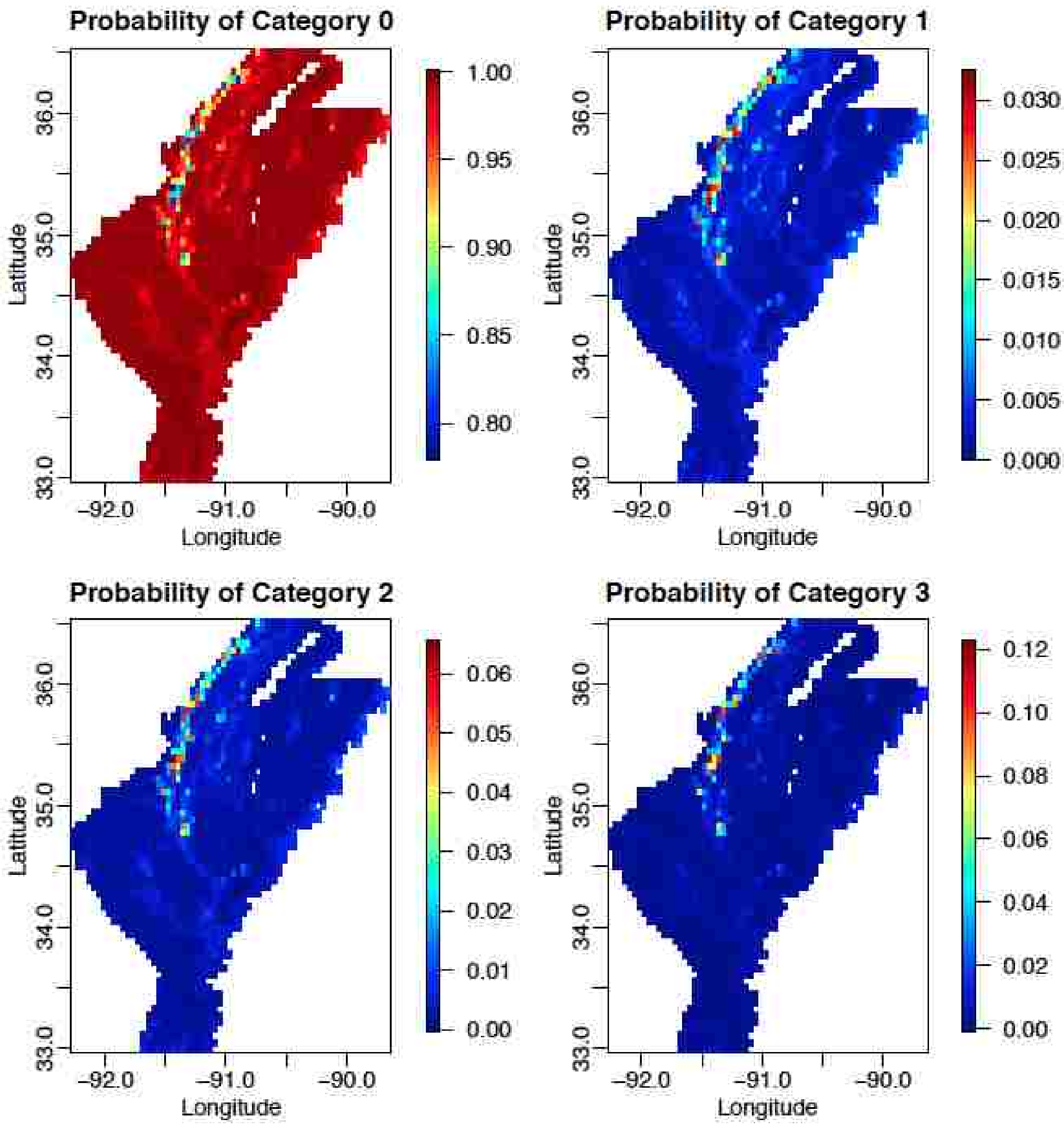

Figure 3. Predicted likelihood probabilities for the distribution of mallard abundance categories. Figure represents the November 2009 survey, from the top within-year model by DIC. 0 - no mallards, Group 1 - 1-15 mallards, Group 2 -16-100 mallards, Group 3 - 100 + mallards.

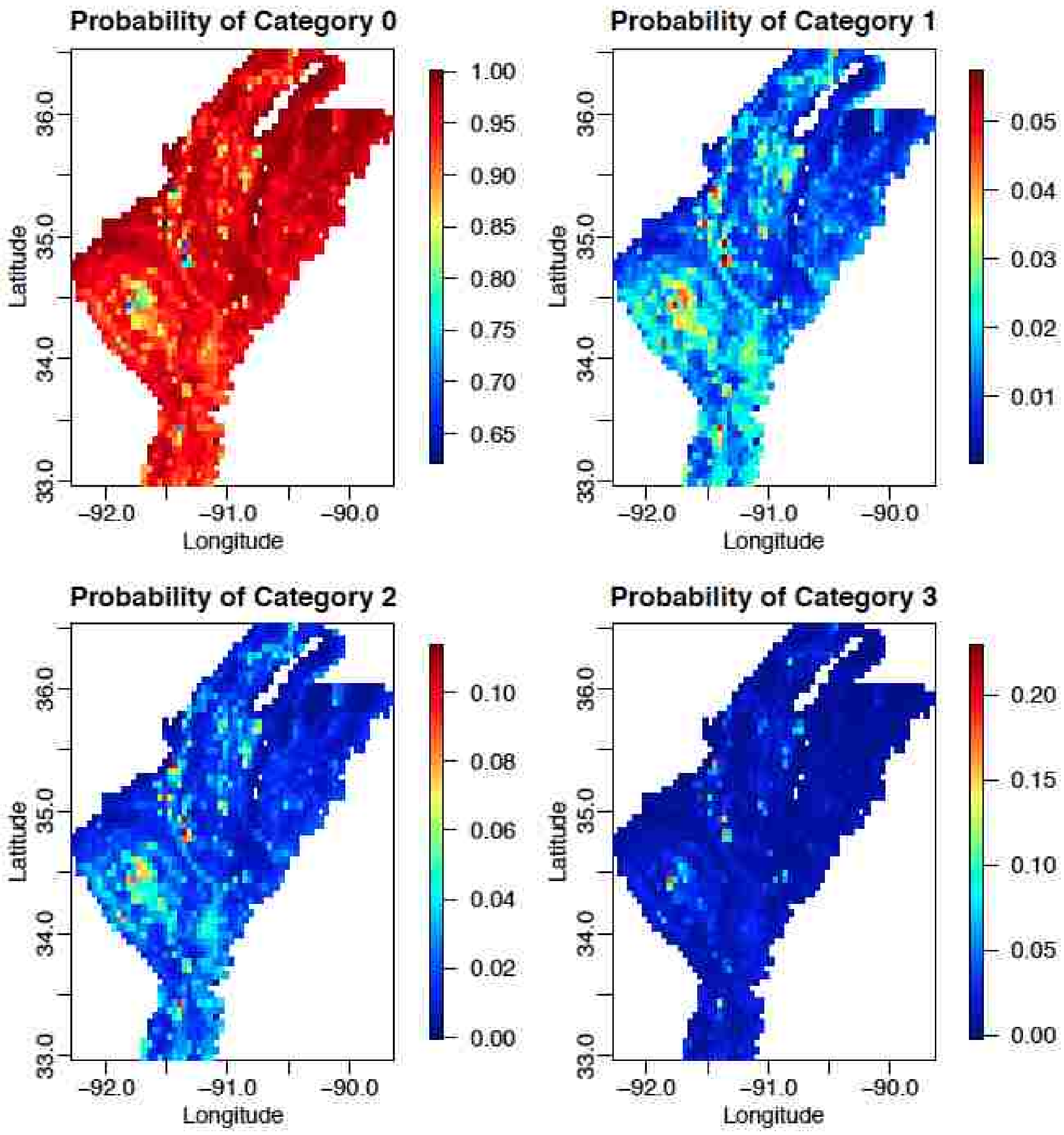

Figure 4. Predicted likelihood probabilities for the distribution of mallard abundance categories. Figure represents the December 2009 survey, from the top within-year model by DIC. 0 - no mallards, Group 1 - 1-15 mallards, Group 2 -16-100 mallards, Group 3 - 100 + mallards.

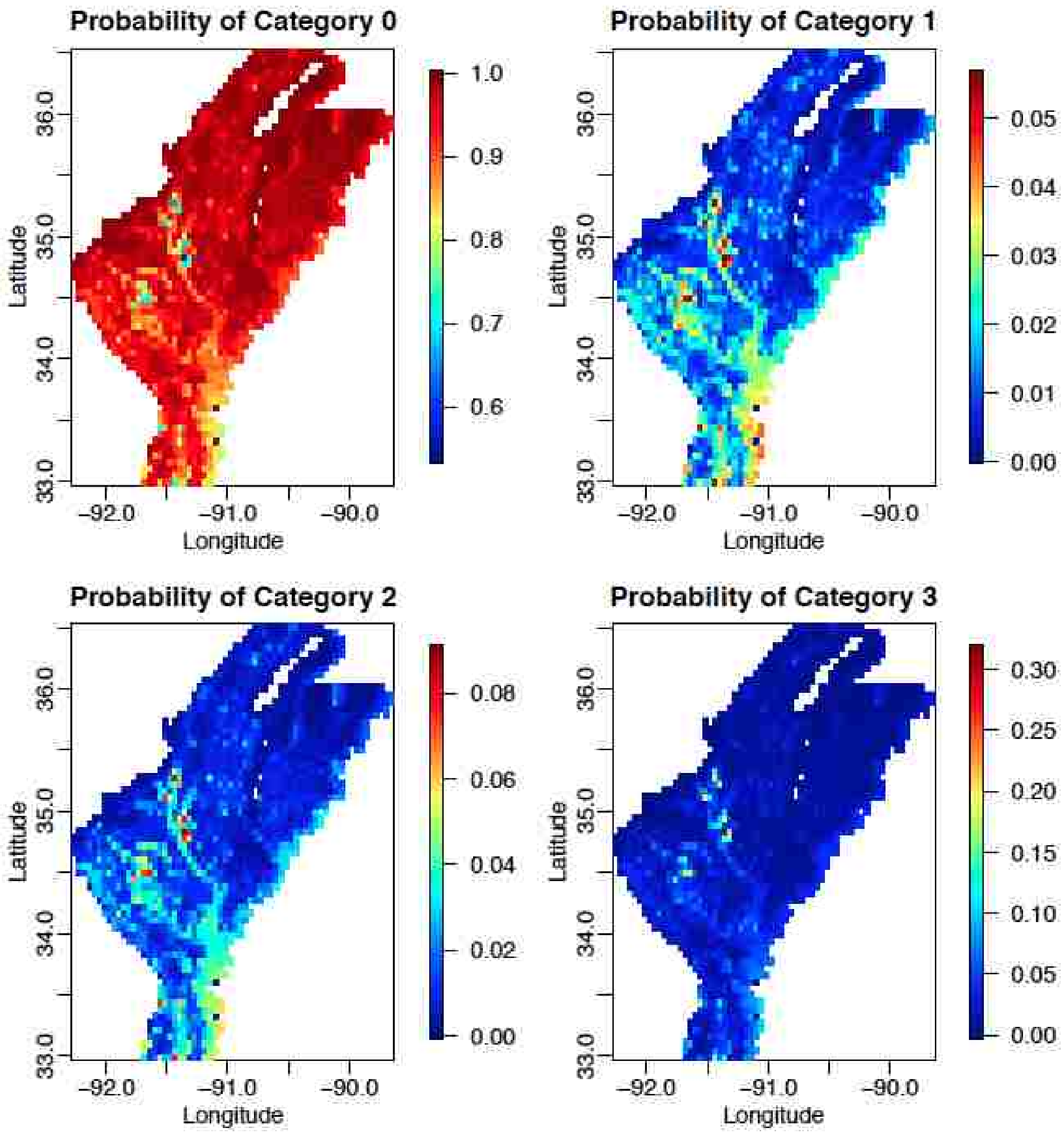

Figure 5. Predicted likelihood probabilities for the distribution of mallard abundance categories. Figure represents the early-January 2010 survey, from the top within-year model by DIC. 0 - no mallards, Group 1 - 1-15 mallards, Group 2 -16-100 mallards, Group 3 - 100 + mallards.

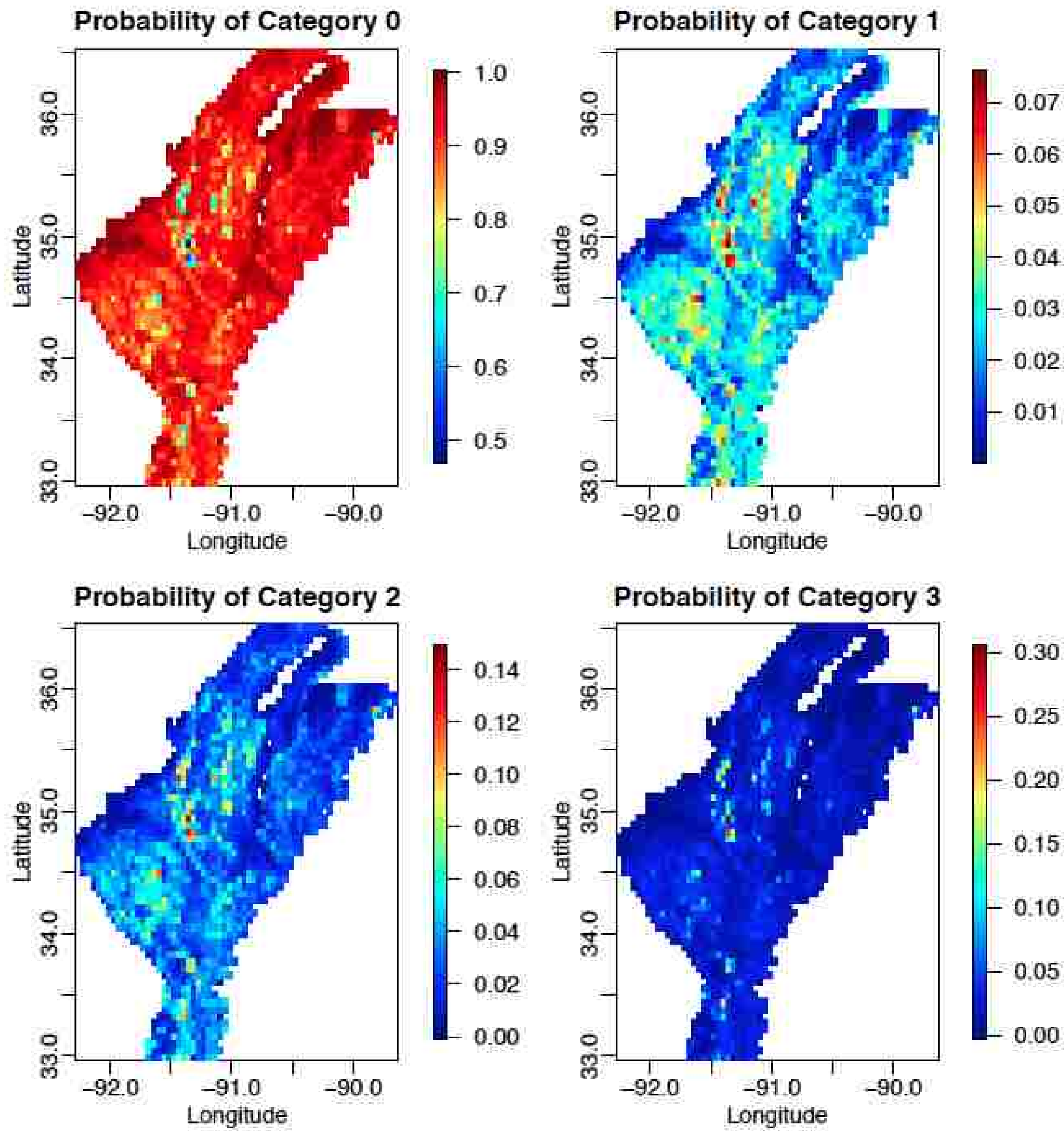

Figure 6. Predicted likelihood probabilities for the distribution of mallard abundance categories. Figure represents the late-January 2010 survey, from the top within-year model by DIC. 0 - no mallards, Group 1 - 1-15 mallards, Group 2 -16-100 mallards, Group 3 - 100 + mallards.

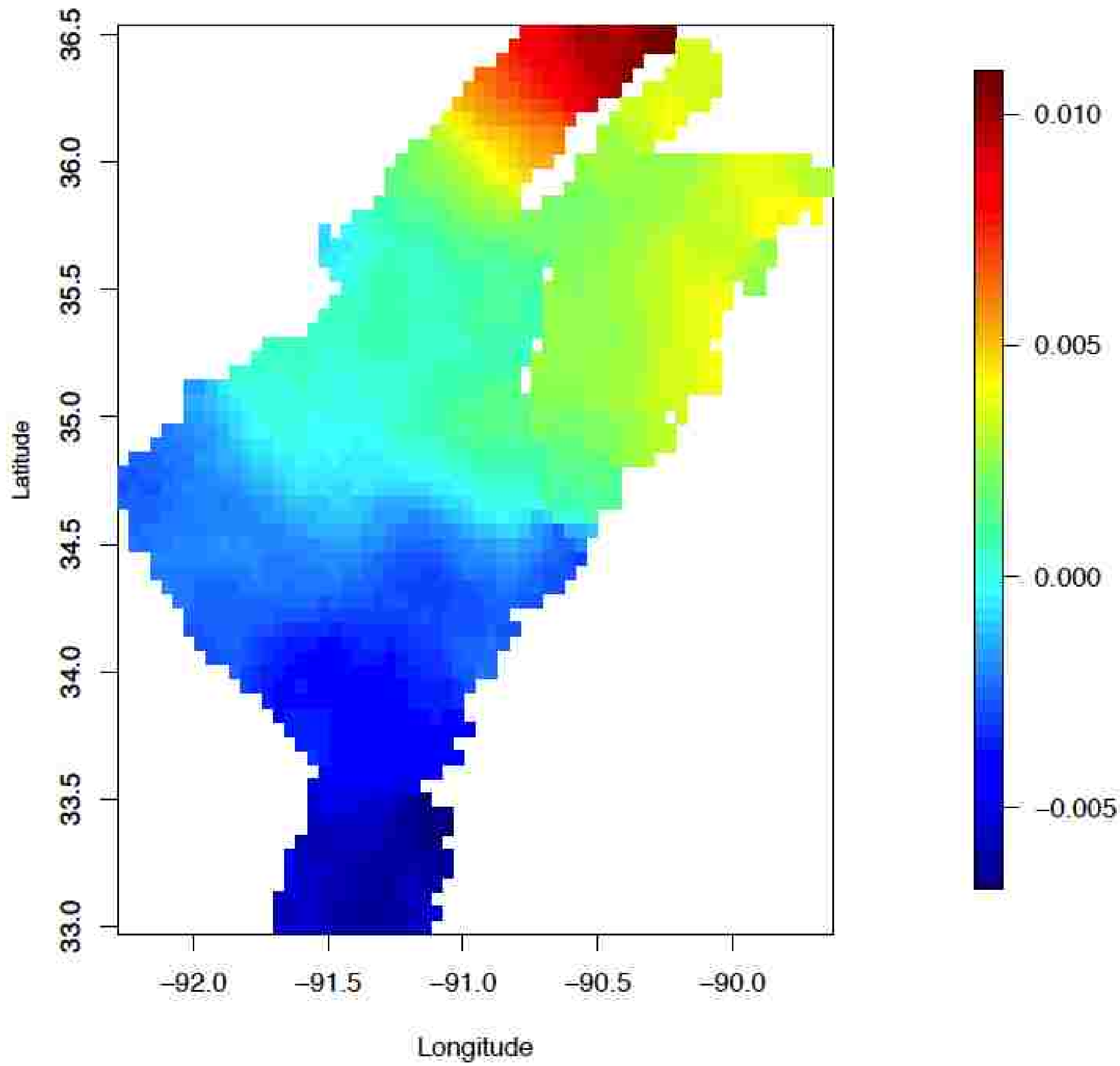

Figure 7. Posterior mean of spatial effects (θ) to account for spatial patterns from factors not represented by the covariates and how mallard abundance is associated with neighboring locations. Figure represents the November 2009 survey, from the top within-year model by DIC.

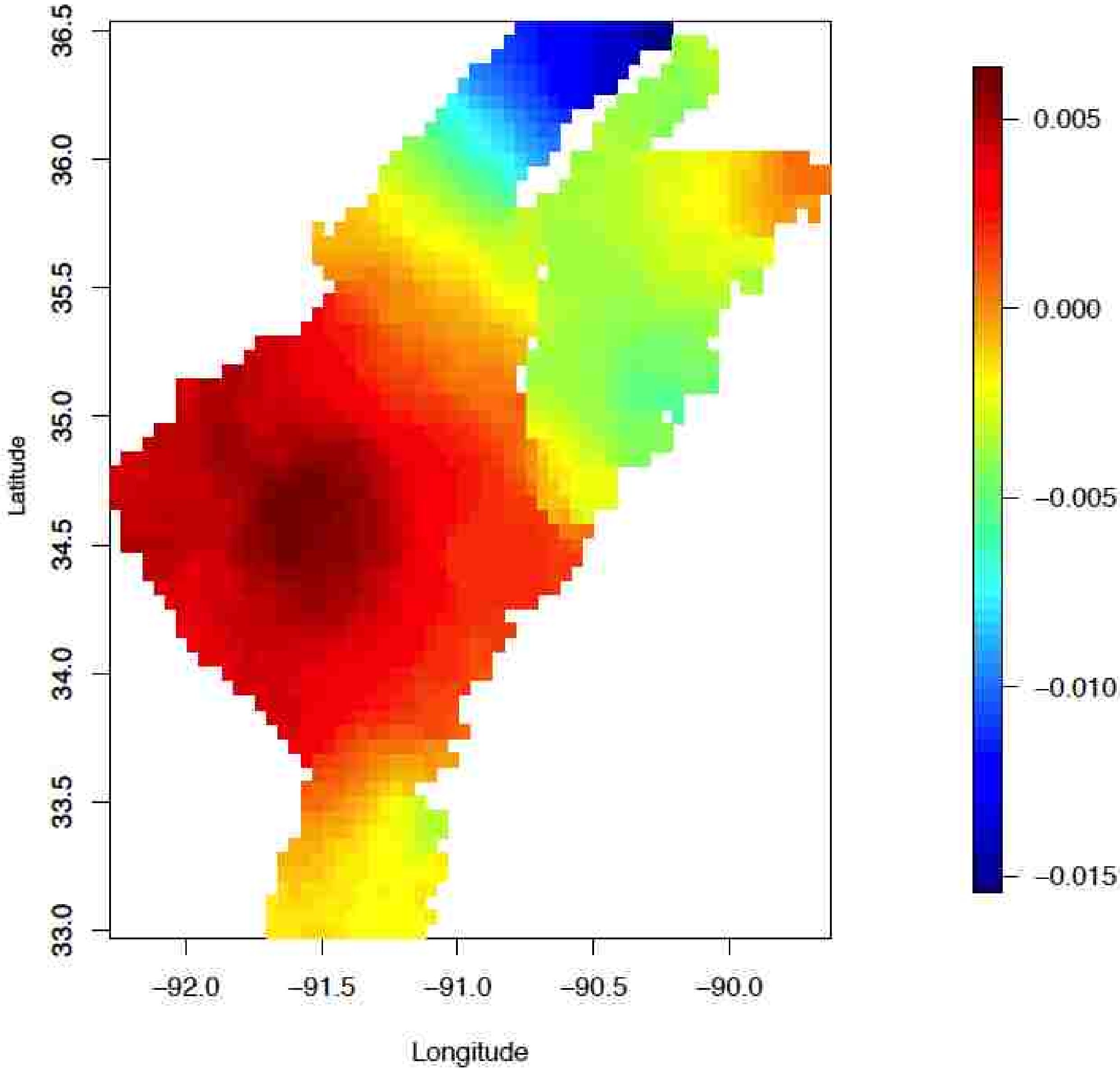

Figure 8. Posterior mean of spatial effects (θ) to account for spatial patterns from factors not represented by the covariates and how mallard abundance is associated with neighboring locations. Figure represents the December 2009 survey, from the top within-year model by DIC.

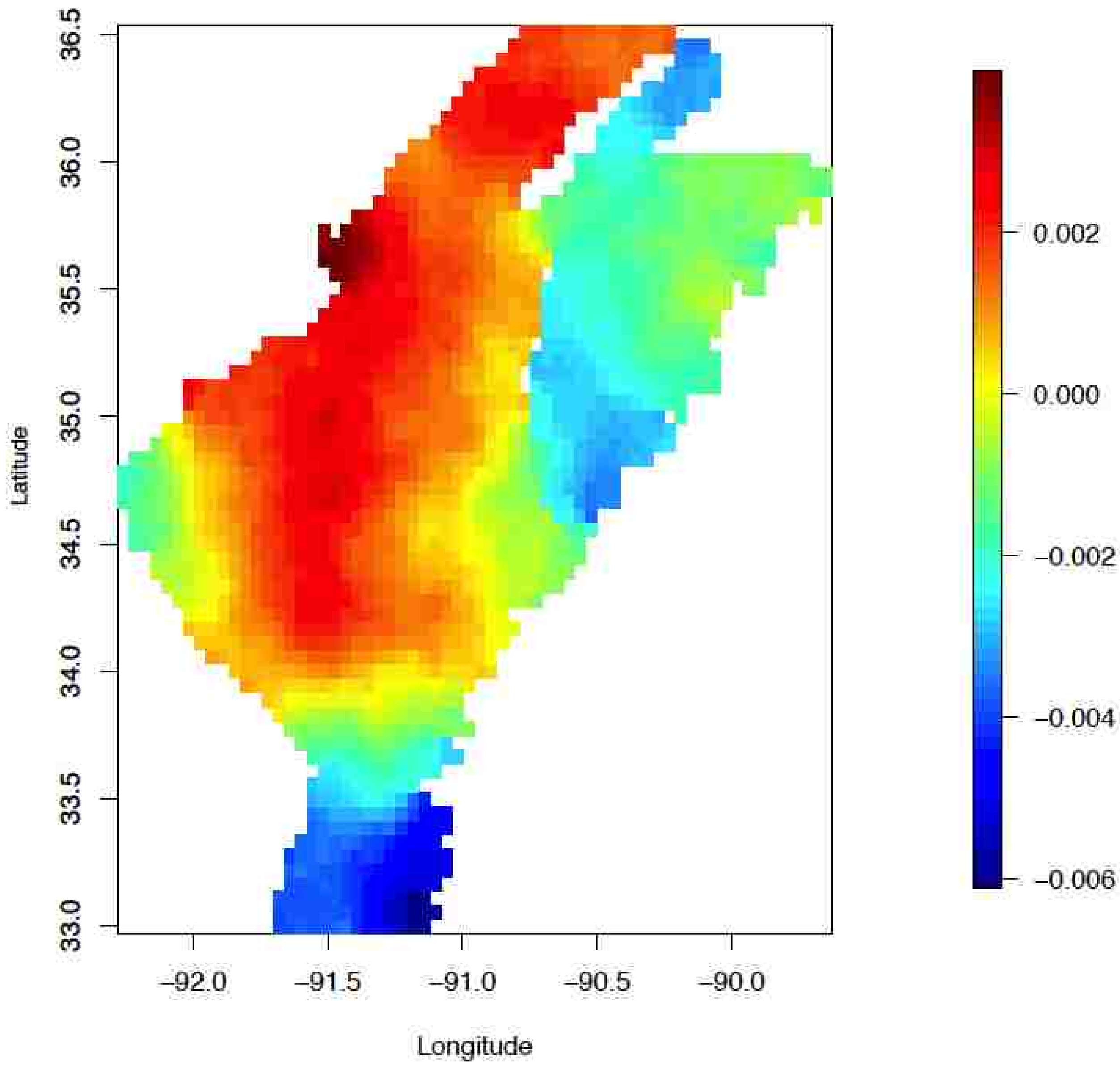

Figure 9. Posterior mean of spatial effects (θ) to account for spatial patterns from factors not represented by the covariates and how mallard abundance is associated with neighboring locations. Figure represents the early-January 2010 survey, from the top within-year model by DIC.

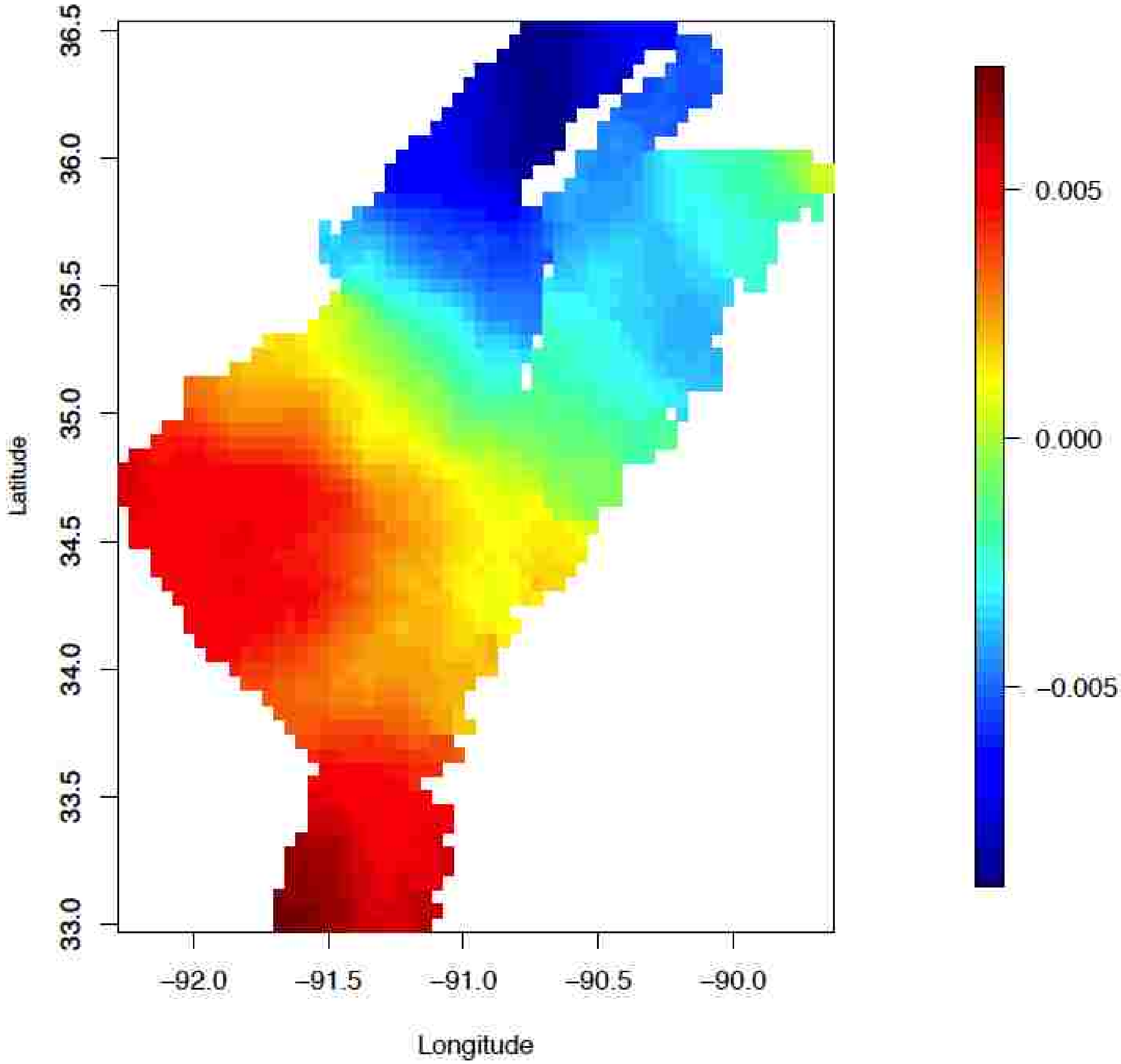

Figure 10. Posterior mean of spatial effects (θ) to account for spatial patterns from factors not represented by the covariates and how mallard abundance is associated with neighboring locations. Figure represents the late-January 2010 survey, from the top within-year model by DIC.

Table 1. Description of covariates used in all models.

Covariate	Description	Data Source
rice field	planted rice in previous summer	CDL[1]
soybean field	planted soybean in previous summer	CDL[1]
corn field	planted corn in previous summer	CDL[1]
fallow field	fallow/idle cropland	CDL[1]
wetland	woody wetland and emergent herbaceous wetland	CDL[1]
open water	permanent water and aquacultures	CDL[1]
surface water	natural and managed winter flooding	Landsat (TM, ETM+, OLI)[2]
managed land	national wildlife refuges (NWR), waterfowl management units (WMU), wildlife management areas (WMA)	AGFC[3]
wetland reserve program		AGFC[3]
winter severity index	Schumner et al. (2010)	Climatological Historical Network
rice production	county level crop yield (kg/ha)	USDA[4]
soybean production	county level crop yield (kg/ha)	USDA[4]
corn production	county level crop yield (kg/ha)	USDA[4]

[1]Cropland Data Layer (CDL) obtained from United States Department of Agriculture (USDA)
[2]Satellites from Landsat satellite program
[3]Boundaries for managed land and Environmental Quality Incentives Program (EQIP) provided by Arkansas Game and Fish Commission
[4]County harvest yield data obtained from USGA

Table 2. Dates and sensor for Landsat image used in surface water extraction.

2009-2010	Nov 17-19	Dec 14-17	early-Jan 4-6	late-Jan 18-21
Path/Row 24/35	3-Nov-2009	5-Dec-2009	None	None
Path/Row 24/36	19-Nov-2009	5-Dec-2009	29-Dec-2009$_{B1}$	None
Path/Row 23/35	12-Nov-2009	28-Nov-2009	none	31-Jan-2010
Path/Row 23/36	12-Nov-2009	28-Nov-2009	none	15-Jan-2010
Path/Row 23/37	12-Nov-2009	22-Dec-2009	none	31-Jan-2010
Path/Row 24/37	19-Nov-2009	5-Dec-2009	29-Dec-2010	none

2010-2011	Nov 11-15	Dec 9-16	early-Jan 27-4	late-Jan 18-21
Path/Row 24/35	14-Nov-2010$_{B1}$	8-Dec-2010	none	none
Path/Row 24/36	14-Nov-2010$_{B1}$	8-Dec-2010	none	2-Feb-2011$_{B1}$
Path/Row 23/35	7-Nov-2010$_{B1}$	1-Dec-2010	2-Jan-2011	26-Jan-2011$_{B1}$
Path/Row 23/36	7-Nov-2010$_{B1}$	1-Dec-2010	2-Jan-2011	26-Jan-2011$_{B1}$
Path/Row 23/37	7-Nov-2010$_{B1}$	17-Dec-2010	2-Jan-2011	26-Jan-2011$_{B1}$
Path/Row 24/37	14-Nov-2010$_{B1}$	none	24-Dec-2011	2-Feb-2012

2011-2012	Nov 14-18	Dec 12-15	early-Jan 1-5	late-Jan16-19
Path/Row 24/35	17-Nov-2011$_{B1}$	3-Dec-2011	4-Jan-2012	None
Path/Row 24/36	17-Nov-2011$_{B1}$	none	4-Jan-2012	None
Path/Row 23/35	10-Nov-2011$_{B1}$	none	28-Dec-2011	29-Jan-2012$_{B1}$
Path/Row 23/36	10-Nov-2011$_{B1}$	12-Dec-2011	28-Dec-2011	29-Jan-2012$_{B1}$
Path/Row 23/37	10-Nov-2011$_{B1}$	12-Dec-2011	28-Dec-2011	29-Jan-2012$_{B1}$
Path/Row 24/37	17-Nov-2011$_{B1}$	None	4-Jan-2012	None

2012-2013	Nov 12-15	Dec 10-12	early-Jan 7-10	late-Jan 21-23
Path/Row 24/35	3-Nov-2012$_{B1}$	13-Dec-2012$_{A}$	6-Jan-2013$_{B1}$	22-Jan-2013$_{B1}$
Path/Row 24/36	3-Nov-2012$_{B1}$	13-Dec-2012$_{A}$	6-Jan-2013$_{B1}$	22-Jan-2013$_{B1}$
Path/Row 23/35	12-Nov-2012$_{B1}$	28-Nov-2012$_{B1}$	7-Jan-2013$_{A}$	31-Jan-2013$_{B1}$
Path/Row 23/36	12-Nov-2012$_{B1}$	28-Nov-2012$_{B1}$	7-Jan-2013$_{A}$	31-Jan-2013$_{B1}$
Path/Row 23/37	12-Nov-2012$_{B1}$	28-Nov-2012$_{B1}$	7-Jan-2013$_{A}$	31-Jan-2013$_{B1}$
Path/Row 24/37	3-Nov-2012$_{B1}$	13-Dec-2012$_{A}$	29-Dec-2012$_{A}$	None

2013-2014	Nov 18-20	Dec 16-19	early-Jan 6-8
Path/Row 24/35	14-Nov-2013$_{C}$	24-Dec-2013$_{B1}$	1-Jan-2014
Path/Row 24/36	13-Nov-2013$_{C}$	24-Dec-2013$_{B1}$	4-Jan-2014
Path/Row 23/35	7-Nov-2013$_{C}$	17-Dec-2013$_{B1}$	25-Dec-2013
Path/Row 23/36	7-Nov-2013$_{C}$	17-Dec-2013$_{B1}$	2-Jan-2014$_{B1}$
Path/Row 23/37	7-Nov-2013$_{C}$	17-Dec-2013$_{B1}$	2-Jan-2014$_{B1}$
Path/Row 24/37	14-Nov-2013$_{C}$	16-Dec-2013$_{C}$	1-Jan-2014

$_{A}$(TM), $_{B}$(ETM+), $_{C}$(OTM).

1 ETM+ image with scan-line correction (SLC) error (Markham et al. 2004).

Table 3. Candidate model set used to explain the abundance and distribution of mallards in the Arkansas portion of the Mississippi Alluvial Valley.

Model	Description
Global	
rice field + soybean field + corn field + fallow field + waste rice + waste soybean + waste corn	Agriculture covariates
rice field + soybean field + wetland + fallow field + permanent water + rice field*surface water + soybean field*surface water + wetland*surface water + fallow field* surface water + WSI	Known land covers that is known preferred habitat of mallards and their interaction with surface water.
wetland + EQIP + managed land + permanent water + wetland*surface water + EQIP*surface water + managed land*surface water + WSI	Land associated with managed land and how managed land interacts with surface water.
surface water + rice field + wetland + permanent water + WSI	Most important covariates for mallards explained in previous research.
surface water + permanent water	Water alone effect on mallard abundance.

Winter Severity Index (WSI) explained in Schumner et al. 2010. WSI only used for within-year models.

Table 4. Top model frequency for covariates affect on mallard abundance and distribution for within-month models from 2009-2014 in the Mississippi Alluvial Valley, Arkansas, USA. Top model indicated by Deviance Information Criterion (DIC), and number indicates the number of times the model ranked as top model in the four annual surveys (n=19).

Candidate Models	November	December	early-January	late-January	Total
Global	0	3	4	0	7
Rice + Fallow + Corn+ Soy+ Rice Production+ Soy Production + Corn Production	0	0	0	0	0
Rice + Soy + Wetland + Fallow + Open Water + Rice*Surface Water + Soy*Surface Water + Wetland*Surface Water + Fallow*Surface Water	5	2	1	4	12
Wetland + EQIP + Managed Land + Open Water + Surface Water + Wetland*Surface Water + EQIP*Surface Water + Managed Land*Surface Water	0	0	0	0	0
Surface Water + Rice + Wetland + Open Water	0	0	0	0	0
Surface Water + Open Water	0	0	0	0	0

Table 5. Significant β estimates from top models for environmental covariates effect on mallard abundance and distribution during individual surveys from 2009-2014 in the Mississippi Alluvial Valley, Arkansas, USA. Models represented are global and land cover + surface water, which were the only top models for the within-year analysis. Total number represents how often the covariate was in the top model, and the combined number of times it had a significant β estimates.

	β direction	November	December	early-January	late-January	Total
Rice	Positive	4	3	4	3	14/19
Soy	Positive	1	1	2	2	6/19
Wetland	Positive	2	4	4	5	15/19
Corn	Positive	0	0	0	0	0/7
Surface Water	Positive	2	2	2	1	4/7
Open Water	Positive	1	4	1	5	11/19
Fallow	Positive	3	3	4	5	15/19
Managed Land	Positive	0	1	1	0	2/7
EQIP	Positive	0	1	1	0	2/7
	Negative	0	0	1	0	1/7
Corn Production	Positive	0	1	1	1	3/7
Rice Production	Positive	0	2	2	1	5/7
Soy Production	Positive	0	1	2	0	3/7
Rice*Surface Water	Positive	1	1	0	2	4/12
Soy*Surface Water	Positive	1	2	1	4	8/12
Wetland*Surface Water	Positive	4	1	1	1	7/12
Fallow*Surface Water	Positive	1	1	0	0	2/12

Table 6. Model ranking by DIC for within-year models, explaining mallard abundance within the Arkansas Mississippi Alluvial Valley. The top-performing model for each year is highlighted in gray.

Year	Global	Agriculture	Habitat+Water	Managed+Water	Important	Water
2009-2010	7457	7878	7448	7675	7515	7640
2010-2011	8343	8726	8325	8535	8410	8651
2011-2012	10056	10491	10072	10145	10169	10345
2012-2013	11533	12031	11513	11722	11712	11876
2013-2014	5706	6019	5752	5789	5801	5923

Table 7. β estimates from top models for covariates that are positively or negatively associated to mallard abundance and distribution during individual winter surveys from 2009-2014 in the Mississippi Alluvial Valley, Arkansas, USA. Numbers represent the frequency an covariate had an association to mallard abundance in the 19 surveys. Models represented are global and land cover + surface water, which were the only top models for the within-year analysis. Total number represents how often the covariate was in the top model, and the combined number of times it had a significant β estimates.

	β	November	December	early-January	late-January	Total
Rice	Positive	4	3	3	4	14/19
Soy	Positive	1	1	1	3	6/19
Wetland	Positive	3	3	4	4	14/19
Corn	Positive	1	0	0	0	1/7
Surface Water	Positive	2	1	1	1	5/7
Open Water	Positive	2	0	2	2	6/19
Fallow	Positive	4	1	4	3	12/19
Managed Land	Positive	1	1	1	0	3/7
EQIP	Positive	0	1	0	0	1/7
Corn Production	Positive	1	1	1	0	3/7
	Negative	0	1	0	0	1/7
Rice Production	Positive	0	0	1	0	1/7
Soy Production	Positive	1	0	1	1	3/7
Rice*Surface Water	Positive	0	2	0	2	4/12
Soy*Surface Water	Positive	1	2	2	3	8/12
Wetland*Surface Water	Positive	3	1	2	2	8/12
Fallow*Surface Water	Positive	0	1	1	0	2/12
WSI	Positive	2	0	1	0	3/19

Negative	0	5	4	4	14/19

Table 8. β estimates for covariates in the within-year models, separated by survey. Only covariates that had beta estimates not overlapping zero influenced mallard abundance in a model, and are the only covariates reported in the table.

November 2009	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Soy Field * Surface Water	3.14	1.85	4.47	0.67	4.72
Wetland * Surface Water	2.88	0.56	5.26	1.21	2.39

December 2009	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Time	0.27	0.072	0.49	0.1	2.57
Rice Field	1.47	0.76	2.22	0.37	3.97
Wetland	1.12	0.46	1.83	0.34	3.32
WSI	-0.22	-0.33	-0.14	0.05	4.61
Rice Field * Surface Water	2.43	0.47	4.37	0.99	2.44
Soy Field * Surface Water	6.5	4.31	8.55	1.09	5.98

early-January 2010	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Time	0.51	0.39	0.65	0.07	7.56
Rice Field	1.09	0.31	1.87	0.41	2.68
Wetland	1.26	0.59	1.96	0.35	3.58
Permanent Water	1.42	0.57	2.23	0.43	3.33
Fallow Field	1.74	0.49	2.98	0.64	2.73
WSI	-0.11	-0.16	-0.06	0.03	4.07
Soy Field * Surface Water	4.3	2.15	6.42	1.08	3.99
Wetland * Surface Water	2.15	0.5	3.86	0.87	2.47

late-January 2010	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Time	0.25	0.15	0.36	0.054	4.58
Rice Field	1.28	0.71	1.86	0.89	4.29
Soy Field	1.26	0.68	1.87	0.3	4.15
Wetland	1.12	0.53	1.71	0.3	3.66
Permanent Water	0.75	0.04	1.44	0.36	2.11
Fallow Field	1.62	0.59	2.66	0.52	3.09
WSI	-0.18	-0.33	-0.02	0.08	2.32
Rice Field * Surface Water	2.49	0.43	4.47	0.103	2.41
Soy Field * Surface Water	2.73	1.48	3.93	0.62	4.37

November 2010	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Rice Field	1.00	0.12	2.05	0.48	2.11
Wetland	1.2	0.37	2.2	0.47	2.57
Fallow Field	2.74	1.22	4.26	0.77	3.54
WSI	0.3	0.21	0.41	0.05	6.07
Wetland * Surface Water	20.98	8.0	34.46	6.77	3.1

December 2010	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Time	0.39	0.16	0.64	0.12	3.16
Wetland	0.72	0.08	1.34	0.32	2.23
WSI	-0.16	-0.23	-0.09	0.04	4.35
Soy Field * Surface Water	4.54	0.19	8.55	2.14	2.12
Fallow Field * Surface Water	28.83	16.57	41.71	6.43	4.48

early-January 2011	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Time	0.32	0.19	0.47	4.58	4.58
Fallow Field	1.15	0.25	2.04	2.52	2.52

WSI	4.64	3.37	5.86	7.38	7.38

late-January 2011	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Time	0.27	0.16	0.38	0.06	4.63
Rice Field	1.93	1.4	2.5	0.28	6.8
Soy Field	1.11	0.53	1.71	0.3	3.65
Wetland	1.01	0.47	1.58	0.28	3.56
Permanent Water	1.13	0.37	1.85	0.38	2.96
Fallow Field	1.23	0.29	2.19	0.48	2.56
WSI	-0.05	-0.08	-0.02	0.02	3.33
Soy Field * Surface Water	5.32	2.31	8.28	1.53	3.49
Wetland * Surface Water	7.12	4.64	9.58	1.27	5.6

November 2011	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Rice Field	1.55	0.6	2.68	0.52	2.98
Corn Field	1.81	0.19	3.41	0.83	2.2
Surface Water	4.05	2.47	5.63	0.82	4.97
Permanent Water	1.85	0.064	3.45	0.84	2.19
Fallow Field	2.53	0.92	4.15	0.84	3.01
Managed Land	7.46	0.093	1.37	0.32	2.32
WSI	3.15	0.22	0.43	0.06	5.63
Corn Production	6.23	0.0002	0.001	0.0002	2.78

December 2011	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Time	0.41	0.28	0.6	0.08	5.04
Rice Field	0.87	0.14	1.52	0.35	2.47
Soy Field	0.93	0.26	1.52	0.32	2.9
Wetland	1.24	0.55	1.86	0.33	3.73
EQIP Land	1.62	0.75	2.6	0.47	3.47
WSI	-0.56	-0.8	-0.4	0.11	5.09
Corn Production	-0.0004	-0.0007	-0.00006	0.0002	2.2

early-January 2012	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Time	0.25	0.15	0.36	0.052	4.92
Rice Field	1.09	0.61	1.57	0.24	4.53
Wetland	0.72	0.24	1.19	0.24	2.97
Surface Water	2.13	1.6	2.65	0.27	8.0
Managed Land	0.6	0.28	0.9	0.16	3.7
WSI	-0.2	-0.34	-0.051	0.075	2.65
Rice Production	0.00004	0.00001	0.00006	0.000013	2.71

late-January 2012	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Time	0.24	0.15	0.34	0.05	4.96
Rice Field	0.88	0.44	1.33	0.23	3.85
Soy Field	0.47	0.052	0.89	0.21	2.23
Wetland	0.64	0.21	1.08	0.22	2.86
Surface Water	208.54	136.75	281.24	37.1	5.6
WSI	-0.15	-0.26	-0.041	0.057	2.69

November 2012	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Rice Field	1.82	1.24	2.42	0.3	6.08
Soy Field	1.13	0.54	1.75	0.31	3.66
Wetland	1.17	0.67	1.69	0.26	4.46
Permanent Water	1.38	0.59	2.19	0.42	3.32
Fallow Field	1.81	0.78	2.58	0.45	3.69
Wetland * Surface Water	7.71	0.73	2.88	0.56	3.28

December 2012	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Rice Field	0.66	0.04	1.27	0.31	2.13
Fallow Field	0.95	0.05	1.82	0.45	2.11
WSI	-0.23	-0.38	-0.1	0.07	3.23
Rice Field * Surface Water	2.9	0.56	5.3	1.21	2.39

Wetland * Surface Water	5.44	3.73	7.19	0.87	6.23

early-January 2013	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Time	0.25	0.13	0.37	0.06	4.3
Rice Field	1.11	0.68	1.53	0.22	5.01
Soy Field	0.52	0.08	0.97	0.22	2.37
Wetland	0.91	0.56	1.27	0.18	5.03
Fallow Field	1.73	1.07	2.39	0.33	5.17
WSI	-0.42	-0.54	-0.3	0.06	6.83
Soy Field * Surface Water	8.0	4.88	11.18	1.6	5.0
Wetland * Surface Water	3.38	0.29	6.45	1.56	2.16
Fallow Field * Surface Water	15.1	7.13	23.31	4.11	3.68

late-January 2013	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Rice Field	0.70	0.17	1.23	0.27	2.6
Wetland	0.57	0.17	0.99	0.21	2.73
Fallow Field	1.59	0.83	2.35	0.39	4.11
WSI	-0.19	-0.25	-0.14	0.03	6.87
Rice Field * Surface Water	1.85	0.6	3.12	0.64	2.89
Soy Field * Surface Water	5.18	3.94	6.41	0.63	8.28
Wetland * Surface Water	0.68	0.02	1.29	0.32	2.09

November 2013	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Rice Field	0.92	0.12	1.73	0.4	2.31
Wetland	1.23	0.48	2.0	0.39	3.14
Surface Water*	4.93	2.98	6.91	1.0	4.92

Fallow Field	1.66	0.48	2.83	0.6	2.77
Soy Production	0.000048	0.00002	0.00008	0.00002	3.03

December 2013	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Time	0.26	0.058	0.45	0.1	2.51
Surface Water	2.39	1.94	2.83	0.23	10.3
Managed Land	0.55	0.2	0.9	0.18	3.04
WSI	-0.33	-0.47	-0.2	0.07	4.76
Corn Production	0.00032	0.0002	0.0005	0.00009	3.61

early-January 2014	Posterior Mean	95% C.I.		Standard Deviation	Mean/SD
Time	0.34	0.2	0.48	0.069	4.89
Wetland	1.88	1.21	2.58	0.35	5.43
Permanent Water	2.01	1.13	2.97	0.46	1.06
Fallow Field	1.24	0.21	2.25	0.52	2.39
Soy Production	0.00004	0.000012	0.00007	0.000016	2.7