EVALUATING FINANCIAL, SOCIAL, AND WATERBIRD IMPLICATIONS OF FARMING WITHIN WETLANDS IMBEDDED IN AGRICULTURAL FIELDS

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

DOCTOR OF PHILOSOPHY

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ABSTRACT

Wetlands of the Prairie Pothole Region (PPR) provide many ecosystem services to the region such as floodwater attenuation, maintenance of water quality, carbon sequestration, and wildlife habitat. The biophysical process characteristics of the region that have made it beneficial for wildlife have also made the region conducive to cultivation; consequently, many wetlands (>49%) in the PPR have been drained and converted to cropland. Although wetlands are often noted for their natural ecosystem services, their contributions to agriculture are often overlooked. Understanding aspects of PPR wetlands, such as value for migrating waterbirds, how wetlands fit into farming operations, and how farmers perceive the fit of those wetlands in their operations will help to find mutually beneficial solutions to wetland management for farmers and conservation efforts.

I evaluated occurrence and densities of various species of waterfowl and shorebirds within agricultural wetlands receiving different manipulations. Most manipulations reduced vegetation heights and proportions of vegetation coverage of the inundated areas of wetlands. Manipulation technique was only important for four species and varied in its effect on density and occurrence probabilities. Most species of waterfowl occurred at higher densities in the low to mid ranges of vegetation coverage.

Based on data collected from farmers, I estimated about half of the area of temporary wetlands and nearly one third of the area of seasonal wetlands are planted on average. Soybean yield and profitability from cultivated portions of temporary wetlands were similar to uplands at average precipitation but were significantly lower in seasonal wetlands. Corn profitability was significantly lower for cultivated portions of temporary and seasonal wetlands for average precipitation conditions. The differences were more pronounced under wetter conditions and

especially when considering the entirety of wetland area, not just the cultivated portions of wetlands.

I examined farmers' perceptions through a questionnaire regarding how they view agricultural wetlands and how wetlands fit into the respondents' farming operations. Despite a low response rate, some informative responses may provide a foundation for further exploration of these data. The results of this dissertation may provide an opportunity for farmers and conservationists to find mutually beneficial management practices for agricultural wetlands.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDIX TABLES

LIST OF APPENDIX FIGURES

CHAPTER 1. GENERAL INTRODUCTION

Studies related to understanding ecosystems services provided by wetlands often focus on conservation lands or more pristine habitat (i.e., wetlands within native or restored grasslands) or areas where access is more easily obtained (Lesser 2001; Hilty and Merenlender 2003; Hargiss and DeKeyser 2014), thus information is generally lacking from privately owned and disturbed areas such as wetlands embedded in cropland. Yet, more than 88% of the land base in North Dakota is privately owned. Cropland, which makes up more than 70% of land in the Drift Prairie of North Dakota (NASS 2017), may still provide ecosystems services to the region. Evaluation of ecosystem services provided by wetlands in cropland is potentially overlooked but can be useful to inform conservation efforts for cropland, which is the largest current land-use type in the Prairie Pothole Region (PPR).

Wetlands of the PPR provide important ecosystem services that are realized throughout the midcontinent of North America (e.g., floodwater attenuation, maintenance of water quality, carbon sequestration, wildlife and livestock forage, and wildlife habitat) (Kirby et al. 2002; Gleason et al. 2008; Brinson and Eckles 2011). Wetlands in the PPR reduce flooding and contribute to water quality on major waterways in North America, such as the Red, Missouri, and Mississippi Rivers (Hey 2002; Zedler 2003; Gleason et al. 2011; Anteau et al. 2016). In the spring and fall, millions of migrating and breeding waterfowl and shorebirds use PPR wetlands for foraging and brood rearing (Kroodsma 1979; Batt et al. 1989; Cox et al. 1998; Euliss et al. 1999; Krapu et al. 2006; Anteau and Afton 2009). Due to the abundance of wetlands in this region, the PPR is breeding habitat for >50% of the North American duck population (Batt et al. 1989).

The pattern of wetting and drying in the region in response to climate variability, which has shaped the plant life and wildlife that use the region (Kantrud et al. 1989; Laird et al. 2003; van der Valk 2005), has provided fertile soils that are also productive for agriculture practices. This productivity has led to an increase in cropland which has significantly altered the landscape. The prairie regions of the United States have lost >75% of its grasslands and >49% of its wetlands (Dahl 1990; Samson and Knopf 1994) primarily due to agricultural expansion. The loss of wetlands has mainly occurred through drainage to convert the basins into agricultural production.

Despite loss of wetlands to drainage, many remaining wetlands are located within privately owned cropland. It is estimated that in the Drift Prairie, a physiographic region within the PPR, 80% of the remaining temporary and seasonal wetlands are located in crop or alfalfa fields (Niemuth et al. 2006). Agricultural wetlands still provide certain ecosystem services, even though they may have altered hydroperiods, manipulated hydrophytes, and cultivated soils. While there has been considerable research on quantifying ecosystem services provided by wetlands (e.g., Daily et al. 2000; Woodward and Wui 2001; Janke et al. 2019; Jenkins et al. 2010; Gascoigne et al. 2011), little attention has been paid to evaluating the ecosystems services provided by agricultural lands and understanding the tradeoffs of services provided by natural and agricultural systems.

Wetlands located in agricultural fields provide foraging habitat for migrating shorebirds and waterfowl (LaGrange and Dinsmore 1989; Niemuth et al. 2006). However, wetlands with more ephemeral hydroperiods are often cultivated when situated within agricultural fields. Farmers employ varying methods to manipulate wetland vegetation in preparation for spring planting which could have impacts on agricultural wetland use by waterbirds. I examined the probability of occurrence and densities of dabbling ducks and shorebirds to assess impacts of vegetation manipulation techniques in comparison to idled agricultural wetlands (Chapter 2). These results could have implications for management practices to increase waterbird use of agricultural wetlands for foraging.

Wetlands of the PPR also provide direct agriculture-related ecosystem services through their agricultural productivity. This aspect of ecosystem services is often overlooked or assessed on willingness-to-pay or cash rent values. However, each of those metrics are approximations and may not represent the true agricultural value of the wetland. Through the analysis of 19 years of precision agricultural data, I examined yields and profits derived from temporary and seasonal wetlands through a corn and soybean rotational cropping system and compared the values to surrounding upland areas (Chapter 3 and 4). These results provided direct and relatable estimates of the value of temporary and seasonal wetlands to farming operations. Understanding more about how wetlands fit into farming operations can provide an opportunity to help farmers be more profitable on less productive areas and protect wetland habitat from further losses.

How landowners view, value, and make decisions on the manipulation of wetlands within their fields influences the wetland's vegetation, hydroperiod, quality, and in turn, its use by wildlife. Yu and Belcher (2011) reported that farmers' attitudes towards wetlands reflected conservation decisions on their land. Many farmers believe that decisions of how land is used is the right of the landowner (Wachenheim et al. 2018). I attempted to evaluate farmers' perceptions and expectations of yield and willingness to continue to cultivate wetlands under various wetland size and financial outcome scenarios when cultivating wetland areas (Chapter 5). The results of the questionnaire provide some insights into perceptions of wetlands and may guide further development and structure of studies to address responses, comments, or concerns of respondents.

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CHAPTER 2. DABBLING DUCKS AND SHOREBIRDS PREFER AGRICULTURAL WETLANDS WITH LESS VEGETATION IN THE DRIFT PRAIRIE OF NORTH DAKOTA AND SOUTH DAKOTA

Abstract

The Drift Prairie historically provided thousands of wetlands used by migrating and nesting shorebirds and waterfowl. The region has been largely converted from grasslands to croplands because of its gently rolling hills, fertile soils, and private ownership. Currently (2022), many of the remaining wetlands are situated within croplands, creating a fragmented landscape. Smaller wetlands within these fields are subject to various direct farming manipulations such as burning, disking, harvesting, and mowing in an effort to establish and harvest crops within wetlands during dry periods. I evaluated the vegetation structure of idled and manipulated agricultural wetlands to investigate whether the management method or resulting vegetation structure was more important to occurrence probabilities and densities of waterfowl and shorebirds. I used linear regressions and a MANOVA to compare the effects of manipulations on wetland vegetation structure. I found that, compared to idled wetlands, all manipulations reduced vegetation heights in inundated areas and all manipulations, except mowing, reduced the proportion of vegetation cover in inundated areas. Disking was the only manipulation to reduce mudflat vegetation heights and coverage proportions. I constructed generalized linear models for shorebird and duck occurrence and densities and performed variable and model selection using AIC_C to determine useful variables and final models from candidate model sets. Management method was an important variable for predicting occurrence of yellowlegs and "any shorebird", but not in other shorebird models. The killdeer model was the only shorebird model to include any vegetation variables to explain variation in either occurrence

or density. Vegetation variables helped explain variance in "any duck", gadwall, mallard, and northern shoveler occurrence probabilities better than management method. Management method helped explain variance in gadwall and northern shoveler densities better than vegetation variables. Harvested wetlands had higher predicted bird estimates than other management method categories. Duck occurrences generally peaked in wetlands with the low to medium (approximately 0 – 0.40) proportion of vegetation coverage, but duck densities steadily decreased as proportion of vegetation coverage increased >0.09 – 0.14. Thus, reducing vegetation within agricultural wetlands is expected to increase use by most migrating dabbling duck and shorebird species.

Introduction

Wetlands in the Prairie Pothole Region (PPR) provide foraging and nesting habitat for millions of waterbirds migrating through and breeding in the mid-continent of North America (Batt et al. 1989; Skagen et al. 1999). These waterbirds rely on interspersed wetlands across their migration routes as foraging habitats to replenish and build their energy reserves. Similarly, nesting waterbirds rely on various wetland types to provide quality foraging resources and vegetative cover throughout the breeding season. The availability and quality of forage resources can influence the body condition of waterbirds, the survival of adults, nests, and juveniles, and recruitment rates (Batt et al. 1989; Cox et al. 1998; Hegyi and Sasvari 1998; Euliss et al. 1999; Krapu et al. 2006; Anteau and Afton 2009). Therefore, breeding and migrating waterbird population levels could be affected by spring wetland abundances and conditions in the PPR (Kaminski and Gluesing 1987; Raveling and Heitmeyer 1989).

The hydrology and natural disturbances of PPR wetlands have been a major factor in the biological productivity of the region. Natural disturbances, such as drought and deluge weather patterns, and soils of the region make PPR wetlands highly productive (Euliss et al. 2004; Mushet 2016). Wetlands of the PPR have generally been classified by hydroperiod, or, the duration water is ponded within the wetland, (Stewart and Kantrud 1971), but function on a continuum based on atmospheric and groundwater water input dynamics (Euliss et al. 2004; Hayashi et al. 2016). Water level dynamics in the PPR are primarily dictated by snow melt and spring rains, which result in temporary wetlands retaining water for short periods (14–28 days) and seasonal wetlands typically holding water for longer periods (30-90 days) (Dahl 2014). Hydroperiod influences many aspects of vegetation within and adjacent to PPR wetlands, including location in the basin and stem densities. In natural settings, temporary wetlands may contain fine-stemmed grasses, sedges, and some forbs, whereas seasonal wetlands may contain more moisture tolerant species, such as wetland grasses, sedges, rushes, and cattails (Stewart and Kantrud 1971). Vegetation in undisturbed wetlands may produce high stem densities that increase aerial vegetative coverage and leave little open or unobstructed surface water which may reduce usable foraging and roosting habitat preferred by certain migrating shorebirds and waterfowl (Weller and Spatcher 1965; Voigts 1976; Kantrud 1990; Anteau 2012). Historically, natural disturbances such as drought and deluge weather patterns, fires, and ungulate grazing resulted in reduced wetland vegetation stem density and biomass which resulted in a mixture of open water and vegetation within wetlands thereby producing a scattered mosaic of vegetation patterns across the PPR landscape. Today, natural disturbances have mostly disappeared because of human activity, including common agriculture practices that have fragmented the PPR landscape.

The climate and soils that make the PPR beneficial for wildlife also make it productive for growing agricultural crops. In 2017, 72% and 67% of land within the PPR of North Dakota and South Dakota, respectively, was considered cropland (NASS 2017). The relatively flat and gently rolling topography of the Drift Prairie, a physiographic region within the PPR, is particularly well-suited for cultivation. As a result, many wetlands in this region are situated within cropland. Niemuth et al. (2006) reported >80% of wetlands in the Drift Prairie of North Dakota were located in crop or alfalfa fields; hereafter I will refer to these wetlands as agricultural wetlands (AW).

While many seasonal and temporary wetlands situated in agricultural fields have been drained by farmers to increase tillable acres (McCauley et al. 2015), those that remain are regularly cultivated. Farmers can often disk and plant crops within temporary wetlands on an annual basis. During extended wet periods, high densities of emergent vegetation (e.g., cattail, reed) may persist in AW. When dry conditions return, farmers may attempt to remove emergent vegetation within AW during autumn. One expected outcome of this practice is to reduce the amount of snow that may accumulate, thus decreasing soil moisture and water levels (LaBaugh et al. 1998; Renton et al. 2015) and making it easier to operate heavy machinery in AW during spring planting. Farmers implement vegetation removal through combinations of burning, disking, and mowing (hereafter referred to as manipulations) (Davis and Bidwell 2008). Frequently AW are cultivated, a process of manipulating them in preparation for planting a crop, planting a crop, or harvesting crop. Some farmers choose to cultivate around AW, leaving them in an “idled” or non-manipulated state. AW left idle, and in combination with the lack of natural disturbance (e.g., grazing or fire), altered hydroperiods, and increased sedimentation, may contain high densities of emergent vegetation.

Recent increases in the conversion of wetlands to cropland have raised concerns regarding the ability of the PPR to continue to provide adequate stopover and refueling habitat for migrating waterbirds (Skagen 1997; Anteau and Afton 2004; Eldridge et al. 2009; Anteau and Afton 2011). Wetland conversions have increased during the past 50 years because of pressure on farmers to expand the amount of land in agricultural production, which can be attributed in part to commodity prices, land values, and government programs and policies (Lark et al. 2015; Brandes et al. 2016). Lands within the PPR have experienced a rapid expansion of cropland, and North Dakota was identified as a 'hotspot' of new cultivation with most of the cropland expansion located east of the Missouri River (Lark et al. 2015). Lark et al. (2015) noted that 55,000 hectares of wetlands were converted to crops in North Dakota, South Dakota, and Minnesota between 2008 and 2012. Additionally, the US PPR has lost between ~32-90% of its wetlands to drainage between the 1850s and the 1980s (Dahl 2014). AW and their associated functions are affected by agricultural practices directly (i.e., manipulated, drained) and indirectly (e.g., increased runoff and sedimentation from agricultural uplands) (Forsyth et al. 1997; Gleason and Euliss 1998). However, these wetlands may continue to serve ecosystem services, such as foraging habitat for waterbirds (LaGrange and Dinsmore 1989; Skagen and Knopf 1994a; Niemuth et al. 2006).

Many variables have been used to predict waterbird use of wetlands, including invertebrate dynamics, vegetation composition and structure, and adjacent land use. Availability of aquatic invertebrates, which are a primary forage for spring migrating waterbirds, is likely an important factor determining use of PPR wetlands by spring migrating waterbirds (Lillie and Evrard 1994). Greater invertebrate abundances have been found in non-tilled than in tilled wetlands (Euliss and Mushet 1999; Knapp 2001) and have been linked to wetland vegetation structure (Lillie and Evrard 1994). Other factors, such as land use, may also influence waterbird selection of wetlands on a broader landscape scale (Taft and Haig 2006a; Taft and Haig 2006b).

Shorebird occurrence in certain wetlands has been negatively associated with the amount of grassland in the surrounding landscape, suggesting a preference for a landscape that is mostly tilled (Skagen et al. 2005). Foraging shorebirds in agriculture landscapes tend to prefer seasonal and temporary wetlands with larger perimeters and lower amounts of emergent vegetation (Niemuth et al. 2006). In contrast, mallards (*Anas platyrhynchos*) migrating through the PPR of Iowa have shown a preference for wetlands that were non-tilled following harvest, vegetated with corn stubble or moist-soil emergent plants, surrounded by non-tilled uplands, and located further from roads (LaGrange and Dinsmore 1989). Although, guilds of waterbirds may prefer different wetland characteristics, AW across the PPR can provide a variety of different wetland habitats with varying vegetation structures.

Agricultural wetland manipulation techniques practiced by farmers in the Drift Prairie result in multiple residual vegetation structures which support different waterbird communities and densities. The extent to which waterbird species occurrences and densities in AW of the Drift Prairie are related to manipulation practices or resulting residual vegetation structures is uncertain. Therefore, I examined the relationship of AW management method (i.e., idled, burned, disked, mowed, or harvested) with spring occurrences and densities of waterfowl and shorebirds in the Drift Prairie of North and South Dakota from 2017–2019. I hypothesized that more species of waterbirds would occur on AW and in higher densities when wetlands have been manipulated as compared to idled because idled wetlands may have high vegetation densities. Model inclusion or exclusion of management method and vegetation characteristics will lend evidence to whether the management method itself or the resulting residual vegetation had greater influence on waterfowl and shorebird occurrences and densities.

Methods

Study Area and Site Selection Procedure

My research was conducted on private lands in the Drift Prairie of eastern North Dakota and South Dakota during 2017–2019. In the Drift Prairie, the highest wetland densities can reach >57/km^2 (Dahl 2014), mainly composed of temporary and seasonal wetlands. Most wetlands are <0.5 ha in area, but can reach sizes of >40 ha for permanent bodies of water (Kantrud et al. 1989; Batt 1996; Niemuth et al. 2010). However, land use in the Drift Prairie is predominantly agriculture. During 2017, 73% and 71% of land from counties fully residing within the Drift Prairie of North Dakota and South Dakota, respectively, was designated as cropland (NASS 2017).

I selected agricultural fields containing surveyed wetlands opportunistically through in-person exploration or information received from communications with landowners. I visually inspected agricultural fields for wetlands that were burned, disked, harvested, idled, or mowed. A field was defined as a unit of land planted as a single continuous crop type and owned or operated by one landowner or landowner group. Thus, field sizes varied across this study. I was granted access to entire fields and all the wetlands contained within the fields. I constrained selection of wetlands so that idled (control) wetlands with similar hydrology were spatially distributed among wetlands manipulated by typical farming practices.

I visited each field twice yearly when spring migrating birds were observed in the area (mid- to late-April), beginning with the southernmost fields in the Drift Prairie for which I had access and progressively moving northward to mimic the spatiotemporal changes in migrating bird communities. I selected different randomly numbered, mapped wetlands to survey each visit to each field without visiting a wetland that had already been surveyed that year. I would visually inspect wetlands for signs of burned vegetation, disked soils, cut or mowed vegetation, harvested crop vegetation, a combination of those manipulations, or no manipulation (i.e., idled). In each field, when a randomly selected wetland was dry or failed to meet management criteria, the closest wetland to meet criteria was used as a replacement. I selected the closest alternative wetland as a replacement to avoid disturbing multiple wetlands on the trek to the next random wetland. I attempted to have idled wetlands within the field or adjacent field for adequate comparisons to manipulated wetlands. Wetland surveys in the same field were conducted more than seven days apart, which was greater than the average length of stay for spring migrating shorebirds (Skagen and Knopf 1994a; Alexander and Gratto-Trevor 1997).

Wetland Surveys

Bird Counts

I conducted surveys between April 17 and May 29 for all years but were timed with the progression of spring waterbird activity (i.e., more species present and higher numbers observed) and open water in agricultural wetlands around Jamestown, ND, which was near the center of the expected survey area. I recorded survey date and later converted date into a spring date index relating to the arrival of the first spring sighting of canvasbacks (*Aythya valisineria*) received from local birders around Jamestown, ND (Larry Igl, Northern Prairie Wildlife Research Center, personal communication). I used this method because canvasbacks typically use larger, more permanent open bodies of water where the progression of ice melt was considered an indicator of spring progression and would be more consistent with their arrival in relation to the progression of spring than other waterfowl species. Also, canvasbacks were less likely to be early migrators or over-winter residents like other waterfowl species such as mallards or Canada geese. Finally, canvasbacks are larger-bodied birds, easily recognizable by many birders making sightings more reliable.

I conducted wetland surveys on foot and used binoculars to count birds at a minimum distance that did not flush the birds. I approached wetlands after the initial count was completed while documenting calls and previously missed birds. I conducted flush counts by walking through vegetation to flush birds in wetlands with standing vegetation. I recorded bird abundance to species with the exceptions of two groups. I combined count data for *Calidris* spp. (i.e., sandpipers) into a "sandpipers" group, because of difficulty in identifying individual species in flocks and at distance. I also grouped *Tringa melanoleuca* and *Tringa flavipes* into a "yellowlegs" category for ease of identification and analysis.

Wetland Vegetation Structure and Characteristics

Immediately after the bird survey, I measured several wetland characteristics and vegetation structure metrics to assess relationships between the avian community and management methods. I recorded the management method (i.e., idled, burned, disked, harvested, or mowed) used by the landowner/operator and cover type category of the wetland in accordance with Stewart and Kantrud (1971). When wetlands were manipulated with multiple techniques (e.g., mowed and then disked), I recorded all manipulations evident and classified the management method as the most prevalent manipulation technique. For example, I classified wetlands that were burned, wholly or in part, as burned even though they may also have been partially disked. I classified a wetland as "harvested" if the wetland had residual, harvested crop vegetation but had no further manipulations such as disking. I did not encounter any wetlands with standing unharvested crops.

I collected a water depth measurement at the approximated center point of each wetland. Four transects on each wetland were extended from the wetland center point outward in the four cardinal directions (north, east, south, west) to the wetland/upland boundary. I recorded the following measurements along each transect: 1) cumulative distance along the transect within the inundated area of the wetland that consisted of <5% aerial vegetation coverage (open water); 2) cumulative distance within the inundated area of the wetland that consisted of >5% aerial vegetation coverage proportion (inundated area vegetation distance); 3) visually estimated aerial vegetation coverage proportion within inundated area of wetland (inundated area vegetation coverage); 4) average vegetation height category (0m, 0-0.5m, 0.5-1m, >1m) within inundated area of wetland (inundated area vegetation height); 5) water depths within the inundated area at 0.5m, 1m, and 3m from the shoreline; 6) cumulative distance of saturated surface soil between the inundated area of the wetland to dry surface soil in the upland (mudflat distance); 7) mean mudflat vegetation height; and 8) mean mudflat aerial vegetation coverage proportion (mudflat vegetation coverage). I included crops or crop residual vegetation in vegetation measurements. I categorized proportions using the following scale: 0-0.05, 0.05-0.25, 0.25-0.50, 0.50-0.75, 0.75-0.95, 0.95-1. I also recorded the distance from the center point out in the four cardinal directions to the wetland perimeter where surface soil was dry (i.e., distance to upland). I used the National Wetlands Inventory (USFWS 2018) and ArcGIS v10.5.1 (ESRI 2019) to calculate the number of palustrine emergent wetlands within 1 km of the surveyed wetland (landscape wetlands).

Statistical Analyses

Management Effects on Wetland Vegetation

I converted all ordinal categorized field measurements to the midpoint value of the range and then averaged those midpoints for each wetland. I tested for correlation among variables using Pearson's correlation coefficient and found there was a strong correlation between average open water and average wetland vegetation coverage ($|r| \leq 0.75$). Consequently, average open water was dropped from further analyses. I examined the influence of management technique on variables related to the vegetation. I used the "Manova" function from the "car" package (Fox and Weisberg 2019) in R (R Core Team 2020) to perform a one-way multivariate analysis of variance (MANOVA) with inundated area vegetation height, inundated area vegetation coverage, mudflat vegetation coverage, and mudflat vegetation height as response variables and management method as the predictor variable. I also performed linear regression for each vegetation variable to management method to further examine this relationship and determine if there were differences in the response variable for each management method. I examined the results using 85% confidence intervals (CI) for all estimates because my model selection process in the bird occurrence and density sections used Akaike's Information Criterion adjusted for small sample size (AIC_C) equating to an 85% confidence interval (Arnold 2010). Effects of the manipulation levels were considered different from the "idled" management level if the CI did not overlap the estimated marginal mean of the "idled" level.

Bird Occurrence

I examined the influence of management method on the occurrence of groups or species of shorebirds and dabbling ducks from 2017–2019 using a generalized linear model (GLM) for a binomial distribution and a logit link (R Core Team 2020). I conducted multiple analyses with different derived responses. "Any shorebird" was a binary response variable indicating the presence or absence of any species of shorebird observed during my counts (American avocet (*Recurvirostra americana*), Wilson's Snipe (*Gallinago delicata*), marbled godwit (*Limosa fedoa*), any sandpiper (*Caladris sp.*), willet (*Tringa semipalmata)*, Wilson's phalarope

(*Phalaropus tricolor*), or any yellowlegs (*Tringa melanoleuca* and *T. flavipes*)). The other modeled response variables were any sandpiper, any yellowlegs, and killdeer (*Charadrius vociferu*), which were selected because they had sufficient occurrences (i.e., at least one presence and absence for each management method) across management methods and wetlands. The number of affirmative occurrences of other shorebird species were too low to accurately model as individual species. Likewise, “any duck” indicated the presence or absence of one of the following dabbling duck species: mallard (*Anas platyrhynchos*), blue-winged teal (*Spatula discors*), gadwall (*Mareca strepera*), northern pintail (*Anas acuta*), or northern shoveler (*Spatula clypeata*). The other models for duck species were constructed with each of the individual dabbling duck species listed above as the binary response variable.

I was primarily interested in how wetland management influenced occurrences and densities by each bird group while controlling for other sources of variation that could be attributed to landscape, temporal changes, hydrology, and vegetation characteristics. I examined the management method effects with independent covariates (Table A.1) for year, spring date index (date), maximum depth of all water measurements (depth), squared maximum depth (depth^2), mean near-shore water depth at 0.5 m in from the shoreline (depth 0.5m), mean near-shore water depth at 1 m in from the shoreline (depth 1m), mean near-shore water depth at 3 m in from the shoreline (depth 3m), circular inundated area of the wetland (inundated area), the coefficient of variation for the near-shore water depth measurements (near-shore depth complexity), number of palustrine emergent wetlands within 1 km (landscape wetlands), mean mudflat distance (mudflat distance), the coefficient of variation for the four center-to-shoreline distance measurements (inundated shape index), the coefficient of variation of the proportion of the wetland that is inundated (proportion inundated), inundated area vegetation height, inundated area vegetation coverage, inundated area vegetation coverage^2, mudflat vegetation height, and mudflat vegetation coverage. I used a natural log transformation for date, area, and near-shore depth complexity variables because we predicted a curved response. I also scaled date, area, inundated shape index, inundated proportion, and near-shore depth complexity variables with the "scale" function in base R to help with potential model convergence issues (Appendix A (Table A.1)). There was no evidence of strong correlation among the unscaled, non-transformed predictor variables ($|r| \leq 0.45$), except the near-shore water depths taken at 0.5m, 1m, and 3m.

Some near-shore water depth measurements, used in the shorebird models, were missing from the dataset (~ 20%) and were replaced by the average of that wetland's remaining depth category measurements. If all of a wetland's measurements for a single depth category were missing, then the average of all wetland measurements for that depth measurement was used as a replacement. The missing data was mainly from the first year of the study and field methods were modified part way through the year. Therefore, this situation fails the assumption of "missing at random" to justify other imputation techniques. Also, because near-shore water depth was a controlling variable and not a variable of interest, using the means would keep the effect of the measured values without losing data because of missing variable information.

Near-shore water depth measurements (depth .5m, depth 1m, depth 3m) were highly correlated and thus, I only selected one of the measurements to include in the next steps full models. For each shorebird group, I evaluated which near-shore water depth measurement provided the best model fit when combined with the full model (i.e., all other possible predictor variables). I selected the model with the lowest AIC_C (Burnham and Anderson 2002) to be the full model in the next step of variable selection. I did not include near-shore water measurements in any of the duck models.

I evaluated predictor variables to remove uninformative variables from the shorebird models with the selected near-shore water variable and from the duck full models using a one-variable-removed selection process where one-variable-removed models were compared to full models using AIC_C (Arnold 2010). If the model AIC_C increased ≥2 points after a predictor variable was removed or ≥4 points when a predictor variable and its quadratic term were removed, then the variable was considered informative and used in the candidate model for that bird group. However, because management method was the predictor variable of interest, I forced it to remain in certain model groups, i.e., it was not a variable that was dropped during the variable selection process. One-variable-removed selection occurred in two modeling groups: management and no management (Appendix A (Table A.2)).

Management — forced inclusion of management method and exclusion of vegetation predictor variables. This group allowed for the best combination of controlling variables to be selected that explained variation without the influence of measured vegetation structure.

No Management — all predictor variables except management method included for one-variable-removed selection. It was possible for vegetation variables to not be included in the resulting candidate model.

The candidate models from these groups were compared to null models using AIC_C to examine their usefulness. The model with the lowest AIC_C score was chosen as the final model. When multiple models were ≤2 AIC_C points from the top model, then the model with the fewest parameters was chosen to avoid overfitting a model for this small dataset.

These model groups allowed me to assess whether management method had greater or additional influence on bird occurrence or density than solely residual vegetation metrics resulting from the management method. A final model which included vegetation variables but not management method would indicate that those vegetation variables included better explained variation than a model which included management method. This would suggest that management method did not influence the outcome variable more than the vegetation variables measured. If management method and no vegetation variables were in the final model then management method would be better at explaining variation in the model than variables from the "No Management" group, which had vegetation predictor variables available in the variable selection process. This would suggest that management method influenced the outcome variable in a way that was not specifically measured or modeled in this study and thus not solely attributed to the measured vegetation variables in this study. When management method was included in the final model, I determined two management methods to be different if the 85% CIs did not include the point estimate of the other management method.

Bird Density

I used the "hurdle" function (Zeileis et al. 2008) from the package "pscl" (Jackman 2010) in R (R Core Team 2020) to model the relationship of shorebird and waterfowl densities to the same predictor variables specified in the occurrence models. A hurdle model was used to account for over-representation of zeros in the count data and because it allows the user to model the zeros in the count data differently than the non-zero counts by specifying separate distributions and predictor variables (Rose et al. 2006; Zeileis et al. 2008; Hu et al. 2011). This modeling framework was composed of two components, a logistic regression (logit link function) where any count is collapsed to a binomial format and a count-based regression (Poisson or negative binomial with a log link function) that omits the zero values. I used predictor variables from the final occurrence models as the predictor variables for the binomial portion of the hurdle model for each bird group. The binomial portion of the hurdle models yielded very similar results as the binomial model conducted in the occurrence section of this study. I modeled them separately for ease of constructing the code to run the one-variable-removed selection in the occurrence models and for the ease of calculating the hurdle density.

I used the natural log of the "inundated area" predictor variable as an offset in the count portion of model which effectively turned the response variable into a density estimate. I used a negative binomial model when Poisson models indicated overdispersion. I used the same one-variable-removed selection process described previously in the occurrence section for the predictor variable selection for hurdle models. However, I conducted predictor variable selection for the hurdle models only on the count (i.e., negative binomial or Poisson) portion of the models because the final occurrence model predictor variables, which had already been through a selection process, were used in the zero portion of the hurdle model.

The hurdle model resulted in a "response density" which was the product of a ratio and a mean (Cameron and Trivedi 2013). The ratio was the probability of non-zero in the zero portion (i.e., binomial) and a non-zero in the untruncated count portion of the model. The mean is from the truncated count of the count portion (i.e., negative binomial or Poisson) of the model. I reported model coefficients for densities from the "count" or zero-truncated (densities >0) portion of the hurdle model hereafter referred to as "truncated density". I reported density estimates on the "response" scale (birds per hectare) as described previously and hereafter designated as "hurdle density".

Results

My analysis included 193 surveyed wetlands from 2017–2019, which had an average depth of 0.27 m (SD = 0.20 m) and an average circular area of 0.867 ha (SD = 1.45 ha). Management methods of wetlands were categorized as idled (n = 62), burned (n = 26), disked (n

= 86), harvested (n = 10), and mowed (n = 9). Blue-winged teal were the most abundant duck species, followed by mallards, gadwall, northern shovelers, and northern pintails (Table 2.1). The most abundant shorebird group was sandpipers followed by yellowlegs, killdeer, American avocet, Wilson's snipe, willet, marbled godwit, and Wilson's phalarope (Table 2.1).

Table 2.1. The number of wetlands in which each species occurred, and the total number of birds counted for each species during springs 2017–2019 within agriculturally-situated wetlands (n = 193) in the Drift Prairie of North Dakota and South Dakota. The species were killdeer (KILL), yellowlegs (YELL), sandpipers (SAPI), blue-winged teal (BWTE), gadwall (GADW), mallard (MALL), northern pintail (NOPI), and northern shoveler (NSHO).

	KILL	**YELL**	**SAPI**	**BWTE**	**GADW**	**MALL**	**NOPI**	**NSHO**
Wetlands	81	35	53	73	54	102	32	41
Birds	199	207	421	373	162	307	71	134

Vegetation Response to Management Method

Results of the one-way MANOVA (Pillai = 0.453, $F_{16,752}$ = 6.002, P < 0.001) suggested the effect of management method on residual vegetation was a better fit than the intercept only model, providing evidence that the means of residual vegetation densities and heights were different between at least two management method. Management method had varying effects on response variables and on individual linear regression responses (Figure 2.1). Each management method (i.e., burned, disked, harvested, or mowed) resulted in lower inundated area vegetation heights than those that were idled (Figure 2.2). Inundated area vegetation coverage was lower for burned, disked, and harvested methods than idled (Figure 2.3). The inundated area vegetation coverage CI for mowed wetlands overlapped the point estimate from the idled level. For mudflat vegetation height (Figure 2.4), only disked wetlands were lower than idled, whereas all other manipulations had CIs which overlapped the point estimate from the idled level. Mudflat vegetation coverage was higher for harvested and mowed than for idled levels of management, whereas disked wetlands showed lower mudflat vegetation coverage than that of idled wetlands

(Figure 2.5). The mudflat vegetation coverage CI for burned wetlands overlapped the point estimate from idled wetlands.

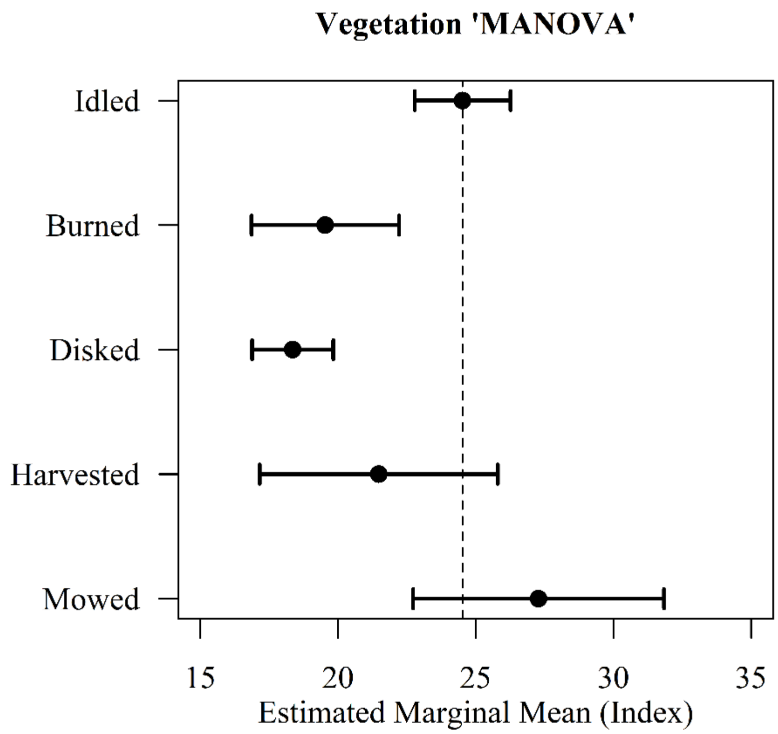

Figure 2.1. Estimated marginal mean index (85% CI) of the inundated area and mudflat vegetation heights and densities from a MANOVA. The dashed vertical line demarcates the mean for idled management method, included for comparison.

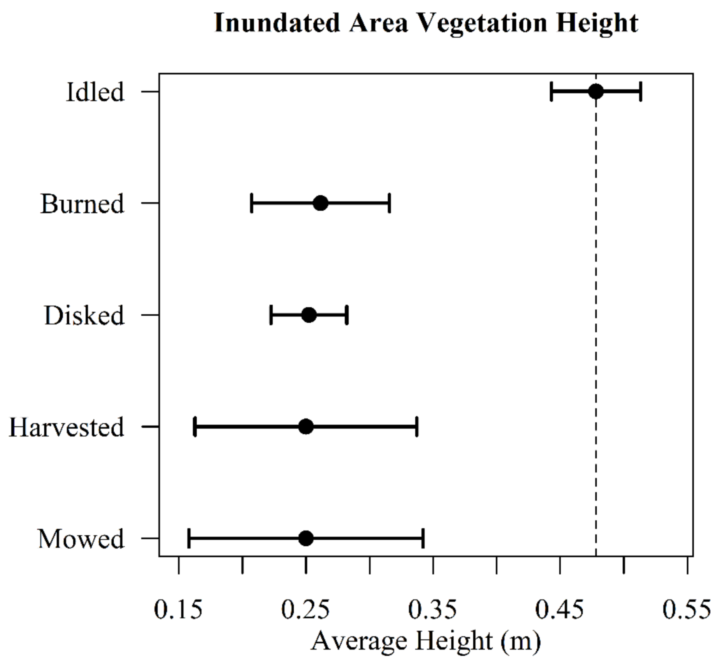

Figure 2.2. Average height (85% CI) of vegetation within the inundated area for each management level. The dashed vertical line demarcates the mean for idled management method, included for comparison.

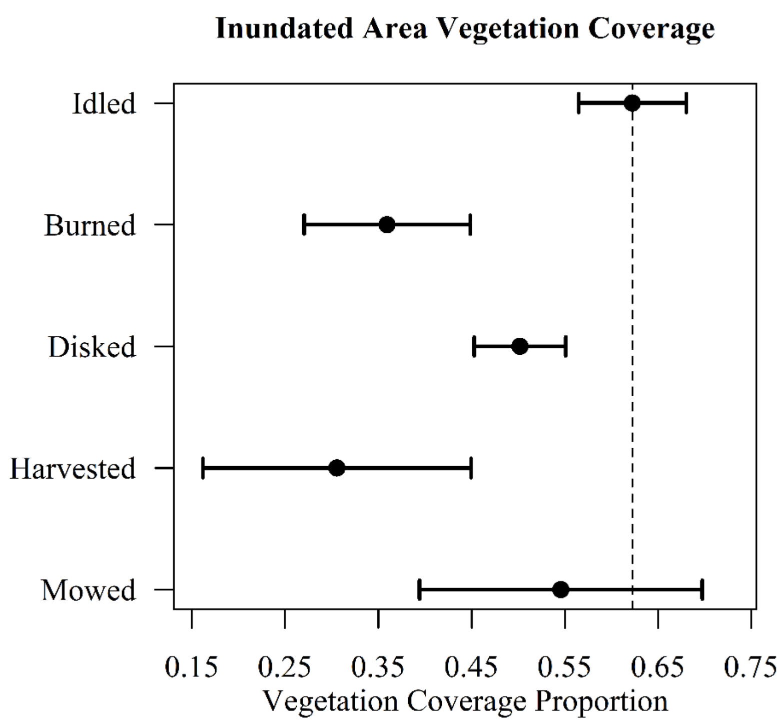

Figure 2.3. The average vegetation coverage proportion (85% CI) within the inundated area for each management level. The dashed vertical line demarcates the mean for idled management method, included for comparison.

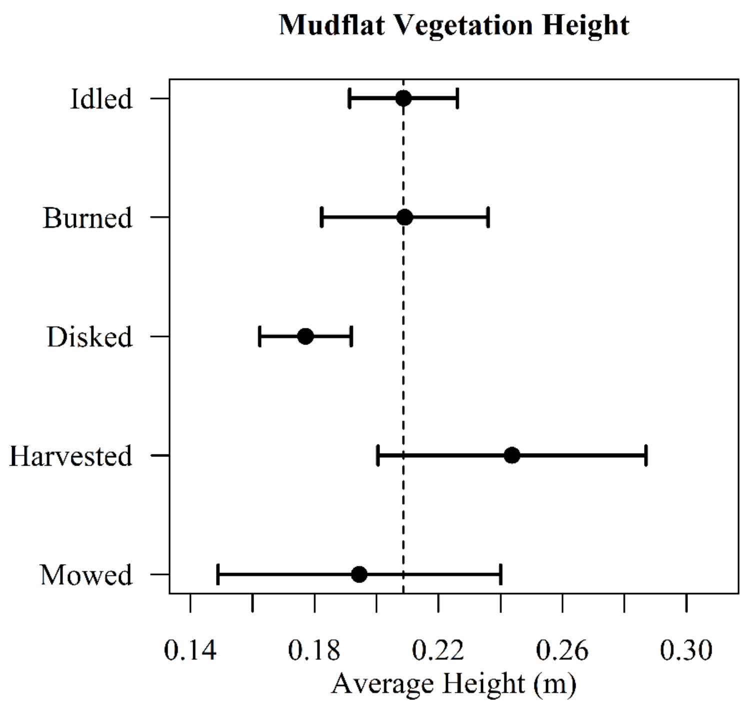

Figure 2.4. Average height (85% CI) of vegetation on mudflats surrounding inundated areas for each management level. The dashed vertical line demarcates the mean for idled management method, included for comparison.

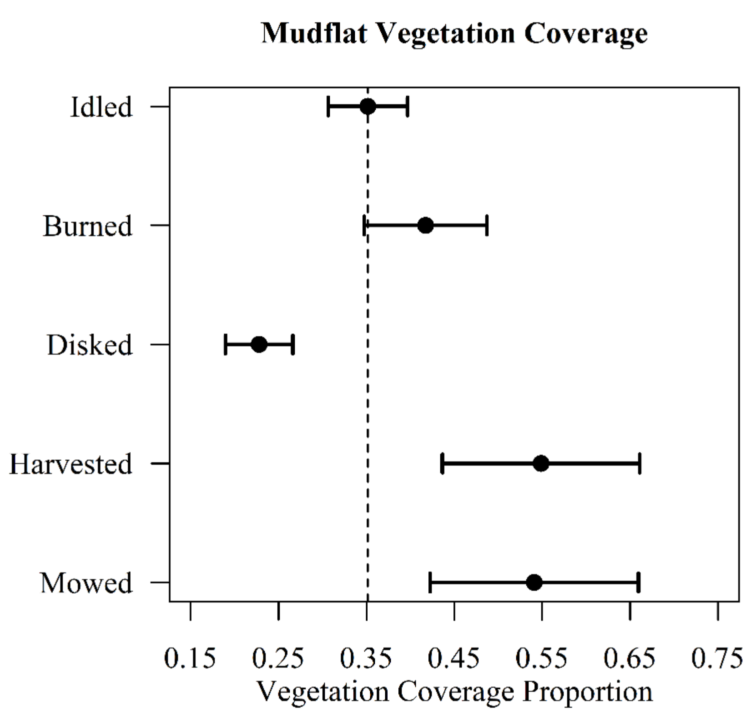

Figure 2.5. The average vegetation coverage proportion (85% CI) on mudflats surrounding inundated areas for each management level. The dashed vertical line demarcates the mean for idled management method, included for comparison.

Shorebird Occurrence

The best fit occurrence model (~100% AIC_C weight; Appendix A (Table A.3)) for the "any shorebird" group came from the "Management" model group. "Any shorebird" had a greater probability of occurrence for disked, harvested, and mowed wetlands than for idled wetlands (Figure 2.6, Appendix A (Table A.4)). The burned level probability of occurrence CI overlapped the point estimate of the idled level. Larger inundated area and greater near-shore depth complexity increased the probability of shorebird occurrence (inundated area $\hat{\beta}$ = 0.481, CI = [0.234, 0.743]; near-shore depth complexity $\hat{\beta}$ = 0.500, CI = [0.265, 0.748]) whereas inundated shape index decreased "any shorebird" occurrence probability ($\hat{\beta}$ = -0.308, CI = [-0.546, -0.076]) (Table 2.2, Appendix A (Table A.5)).

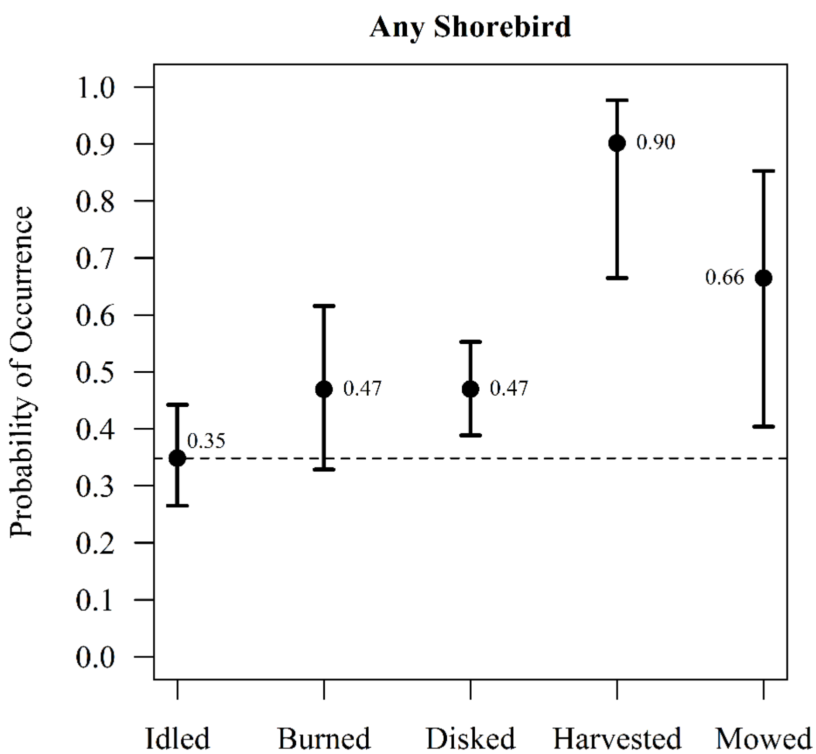

Figure 2.6. Probability of occurrence (85% CI) of "any shorebird" for each wetland management method during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota. The dashed horizontal line demarcates the idled management level mean estimate.

Table 2.2. Final shorebird occurrence (Occ) and density (Den) models and included predictor variables with their associated $\hat{\beta}$ coefficients signs (+/-) relative to the model intercept. Only predictor variables included in the final model had representative signs. The * symbol indicates the corresponding 85% confidence interval excludes 0. The value in the intercept row indicates base levels of categorical predictor variables included in the intercept coefficient estimate.

	Any Shorebird		**Killdeer**		**Sandpipers**		**Yellowlegs**	
Variable	**Occ**	**Den**	**Occ**	**Den**	**Occ**	**Den**	**Occ**	**Den**
Null		x						x
(Intercept)	Idled			Year2017	Year2017	Year2017	Idled & Year2017	
Burned	+						+*	
Disked	+						+	
Harvested	+*						+*	
Mowed	+*						+	
Year2018				+*	-*	+	-	
Year2019				-	-*	-*	+*	
Depth				+*				
Date				+*	+*		-*	
Inundated shape	-*				-*			
Inundated area	+*		+*	-*	+	-*	+*	
Landscape wetlands				-*		-*		
Near-shore depth complexity	+*					+*	+*	
Proportion Inundated				+*				
Mudflat distance								
Inundated area veg height				-*				
Inundated area veg coverage			-*					
Mudflat veg coverage			-					
Mudflat veg height								
Depth .5m								
Depth 1m								
Depth 3m								

For killdeer occurrence, the best fit occurrence model was produced from the "No Management" model group (~100% AIC_C weight, Appendix A (Table A.3)). The management method variable was not included in the final selected model to explain variation in killdeer occurrence (Table 2.2, Appendix A (Table A.5)). Killdeer had a higher probability of occurrence as inundated area increased ($\hat{\beta}$ = 0.481, CI = [0.234, 0.743]) whereas higher inundated area vegetation coverage decreased killdeer occurrence probability ($\hat{\beta}$ = -0.019, CI = [-0.027, -0.012]). Mudflat vegetation coverage had a weak and uncertain effect on occurrence ($\hat{\beta}$ = -0.005, CI = [-0.014, 0.003]).

For sandpiper occurrence, the best fit model was produced from the "No Management" model group, which accounted for ~85% AIC_C model weight (Appendix A (Table A.3)). The management method variable was not included in the final selected model to explain variation in sandpiper occurrence (Table 2.2, Appendix A (Table A.5)). Increased inundated shape index decreased the probability of sandpiper occurrence ($\hat{\beta}$ = -0.309, CI = [-0.596, -0.037]) whereas occurrence probability increased with later sampling dates ($\hat{\beta}$ = 0.693, CI = [0.348, 1.056]). Inundated area had a weak and uncertain effect on the probability of occurrence for sandpiper species ($\hat{\beta}$ = 0.191, CI = [-0.059, 0.450]). The average occurrence probability was highest in 2018 (0.404, CI = [0.324, 0.490]) followed by 2017 (0.225, CI = [0.126, 0.367]) and 2019 (0.101, CI = [0.057, 0.172]).

For yellowlegs occurrence, the "Management" model group produced the best fit model, which accounted for ~100% AIC_C model weight (Appendix A (Table A.3)). Yellowlegs had a greater probability of occurrence on burned and harvested wetlands than on idled wetlands (Figure 2.7, Appendix A (Table A.4)). Disked and mowed management levels had CIs which overlapped the point estimate from the idled level. Increased inundated area and greater near-shore depth complexity increased the probability of yellowlegs occurrence (inundated area $\hat{\beta}$ = 0.579, CI = [0.212, 0.969], near-shore depth complexity $\hat{\beta}$ = 0.859, CI = [0.435, 1.333]) whereas later dates decreased probabilities ($\hat{\beta}$ = -1.474, CI = [-2.067, -0.942]; Table 2.2, Appendix A (Table A.5)). The probability of occurrence was highest in 2017 (0.557, CI = [0.338, 0.755]) followed by 2019 (0.300, CI = [0.140, 0.530]) and 2018 (0.087, CI = [0.043, 0.167]).

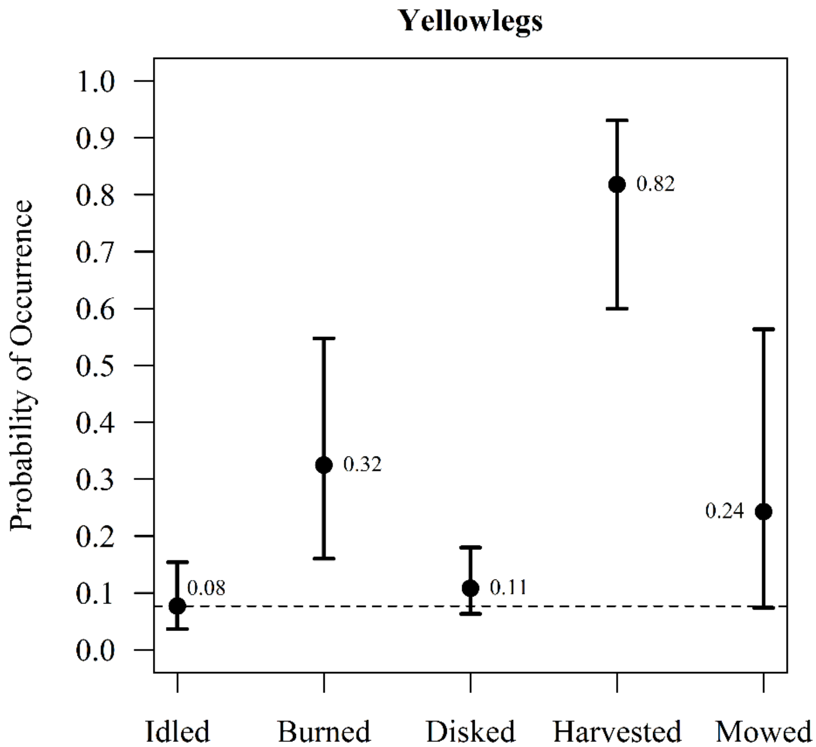

Figure 2.7. Probability of occurrence (85% CI) of yellowlegs for each wetland management method during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota. The dashed horizontal line demarcates the idled management level mean estimate.

Shorebird Density

For "any shorebird" density, the null model was the best fit model from the modeling groups (74% AIC_C weight, Appendix A (Table A.6)). Thus, management method was not an important predictor variable for the "any shorebird" density model in this study (Table 2.2).

For killdeer density, Poisson models were used because they accounted for dispersion of density data better than a negative binomial model. The best fit model (~100% AIC_C weight, Appendix A (Table A.6)) was produced from the "No Management" model group and did not include management method as a predictor variable. Increased proportion inundated, depth, and date increased the truncated density of killdeer (proportion inundated $\hat{\beta} = 0.512$, CI = [0.340, 0.684], depth $\hat{\beta} = 1.231$, CI = [0.607, 1.854], date $\hat{\beta} = 0.421$, CI = [0.237, 0.605]).

Increased inundated area veg height, landscape wetlands, and inundated area decreased the truncated density of killdeer (inundated area veg height $\hat{\beta}$ = -2.214, CI = [-3.191, -1.238], landscape wetlands $\hat{\beta}$ = -0.018, CI = [-0.023, -0.012], inundated area $\hat{\beta}$ = -0.660, CI = [-0.780, -0.540];Table 2.2, Appendix A (Table A.7)). Higher hurdle density of killdeer was estimated for 2018 (1.469, CI = [1.195, 1.744]) followed by 2017 (0.792, CI = [0.588, 0.996]) and 2019 (0.759, CI = [0.616, 0.903]).

For sandpiper density, the best fit model was produced from the "No Management" model group, which comprised 79% AIC_C model weight (Appendix A (Table A.6)). Management method was not included in the final model to explain variation in sandpiper density. More landscape wetlands and larger inundated area decreased truncated sandpiper density (landscape wetlands $\hat{\beta}$ = -0.013, CI = [-0.021, -0.005], inundated area $\hat{\beta}$ = -1.002, CI = [-1.298, -0.706]) whereas greater near-shore depth complexity increased truncated density of sandpipers ($\hat{\beta}$ = 0.694, CI = [0.302, 1.085];Table 2.2, Appendix A (Table A.7)). Higher hurdle densities of sandpipers were estimated in 2018 (5.675, CI = [4.287, 7.063]) followed by 2017 (2.907, CI = [1.186, 4.628]) and 2019 (0.549, CI = [0.244, 0.855]).

For yellowlegs density, the null model (~41% AIC_C weight, Appendix A (Table A.6)) was chosen because it was <2 AIC_C points from the top model and included fewer predictor variables. Management method was not included as a predictor variable (Table 2.2, Appendix A (Table A.7)).

Duck Occurrence

For the "any duck" occurrence, the "No Management" model group had the lowest overall AIC_C score (~97% AIC_C weight, Appendix A (Table A.8)) and management method was not included in the best fit model. Later dates and larger inundated area increased the probability of “any duck” occurrence (date $\hat{\beta}$ = 0.487, CI = [0.220, 0.763], inundated area $\hat{\beta}$ = 1.027, CI = [0.721, 1.359]; Table 2.3, Appendix A (Table A.9)). Probability of “any duck” occurrence was highest at ~0.32 inundated area vegetation coverage (Figure 2.8){inundated area vegetation coverage ($\hat{\beta}$ = 0.044, CI = [0.011, 0.078]); inundated area vegetation coverage^2 ($\hat{\beta}$ = -6.793e-04, CI = [-1.010e-03, -3.590e-04])}.

Table 2.3. Final duck occurrence (Occ) and density (Den) models and included predictor variables with their associated $\hat{\beta}$ coefficients signs (+/-) relative to the model intercept. Only predictor variables included in the final model had representative signs. The * symbol indicates the corresponding 85% confidence interval excludes 0. The value in the intercept row indicates base levels of categorical predictor variables included in the intercept coefficient estimate.

	Any Duck		**BWTE**		**GADW**		**MALL**		**NOPI**		**NOSH**	
Variable	**Occ**	**Den**	**Occ**	**Den**	**Occ**	**Den**	**Occ**	**Den**	**Occ**	**Den**	**Occ**	**Den**
Null												
(Intercept)						Idled						Idled
Burned						-*						+*
Disked						-*						+*
Harvested						+						+*
Mowed						-*						+
Year2018												
Year2019												
Depth		+*	+*						+*			
Depth^2		-*	-*						-*			
Date	+*		+*	-*		-*						
Proportion inundated									+*			
Inundated area	+*	-*	+*	-*		-*	+*	-*	+*	-*	+*	-*
Landscape wetlands												
Inundated shape												
Inundated area veg coverage	+*	-		+	-		+*	-*		-*	+	
Inundated area veg coverage^2	-*	-		-	-		-*	+		+*	-*	
Inundated area veg height					+*							

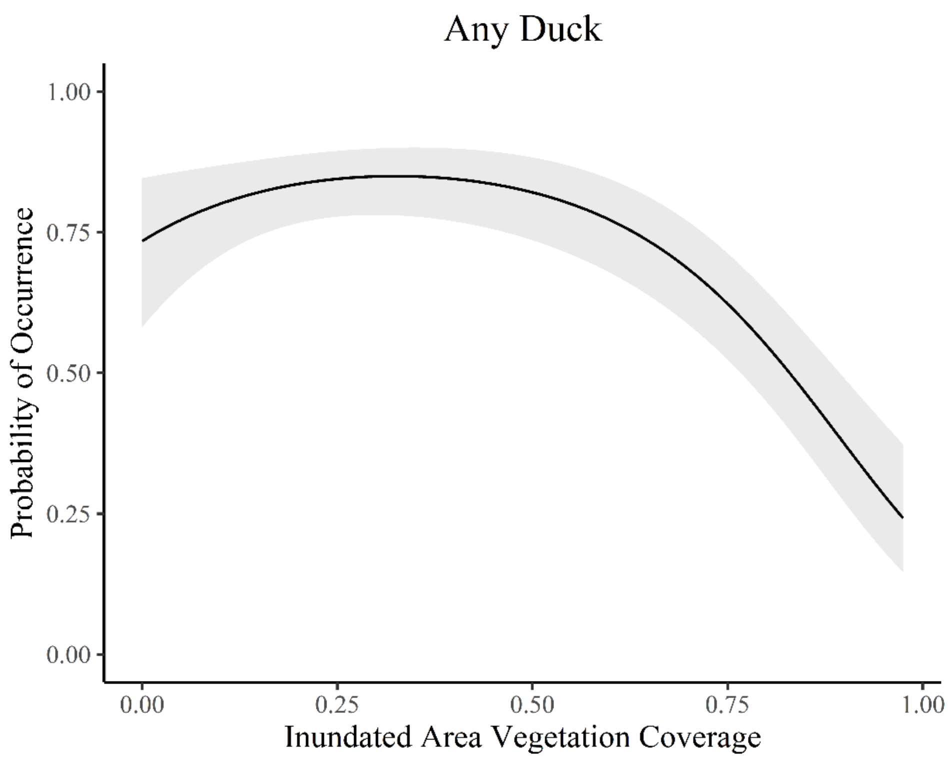

Figure 2.8. Probability of occurrence estimates (85% CI) of “any duck” relative to the inundated area vegetation coverage proportion during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota.

For blue-winged teal occurrence, management method was not included in the best fit model (Table 2.3, Appendix A (Table A.9)). The “No Management” model group produced the best fit model which had the lowest overall AIC_C scores (90% AIC_C weight, Appendix A (Table A.8)). Later spring date and increased inundated area increased the probability of blue-winged teal occurrence (date $\hat{\beta}$ = 0.438, CI = [0.202, 0.681], inundated area $\hat{\beta}$ = 0.556, CI = [0.278, 0.848]). For the depth parameters, the highest probability of occurrence for blue-winged teal occurred at ~ 0.85 m {depth ($\hat{\beta}$ = 7.720, CI = [4.170, 11.341]); depth^2 ($\hat{\beta}$ = -4.562, CI = [-8.200, -0.729])}(Appendix A (Table A.9)).

For gadwall occurrence, management method was not included in the best fit model (Table 2.3, Appendix A (Table A.9)). The “No Management” model group produced the best fit model (~60% AIC_C weight, Appendix A (Table A.8)). Increased inundated area vegetation height increased the probability of occurrence ($\hat{\beta}$ = 2.614, CI = [1.240, 4.037]; Appendix A (Table A.9)). The highest occurrence probability related to inundated area vegetation coverage proportion was near 0 and decreased as inundated area vegetation coverage increased (Figure 2.9){inundated area vegetation coverage ($\hat{\beta}$ = -0.006, CI = [-0.037, 0.025]); inundated area vegetation coverage^2 ($\hat{\beta}$ = -1.876e-04, CI = [-5.036e-04, 1.212e-04])}.

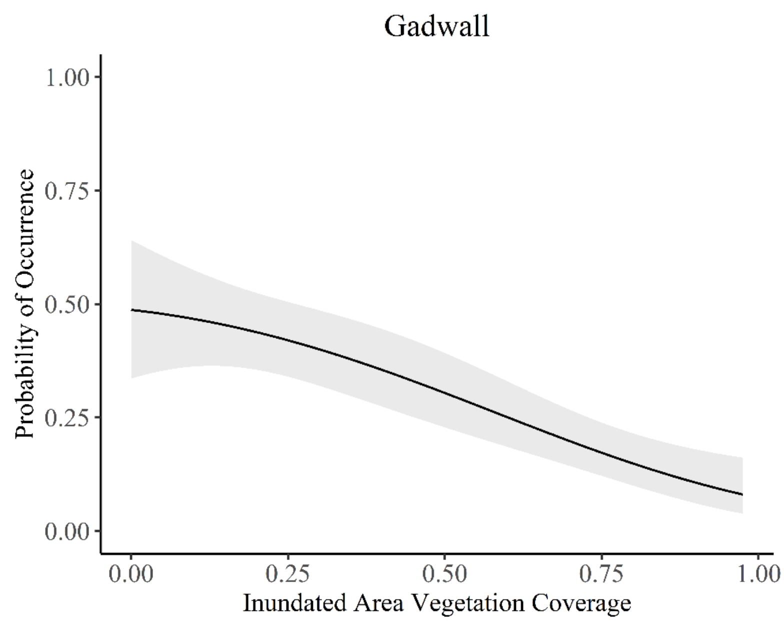

Figure 2.9. Probability of occurrence estimates (85% CI) for gadwall relative to the inundated area vegetation coverage proportion during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota.

For mallard occurrence, management method was not included in the best fit model (Table 2.3, Appendix A (Table A.9)). The "No Management" model group produced the best fit model which had the lowest overall AIC$_C$ scores (~98% AIC$_C$ weight, Appendix A (Table A.8)). Larger inundated area increased the probability of mallard occurrence ($\hat{\beta}$ = 0.693, CI = [0.440, 0.961]; Appendix A (Table A.9)). The highest probability of occurrence related to inundated area vegetation coverage was at ~0.40 inundated area vegetation coverage (Figure 2.10){inundated area veg coverage ($\hat{\beta}$ = 0.042, CI = [0.014, 0.072]); inundated area vegetation coverage^2 ($\hat{\beta}$ = -5.237e-04, CI = [-8.103e-04, -2.440e-04])}.

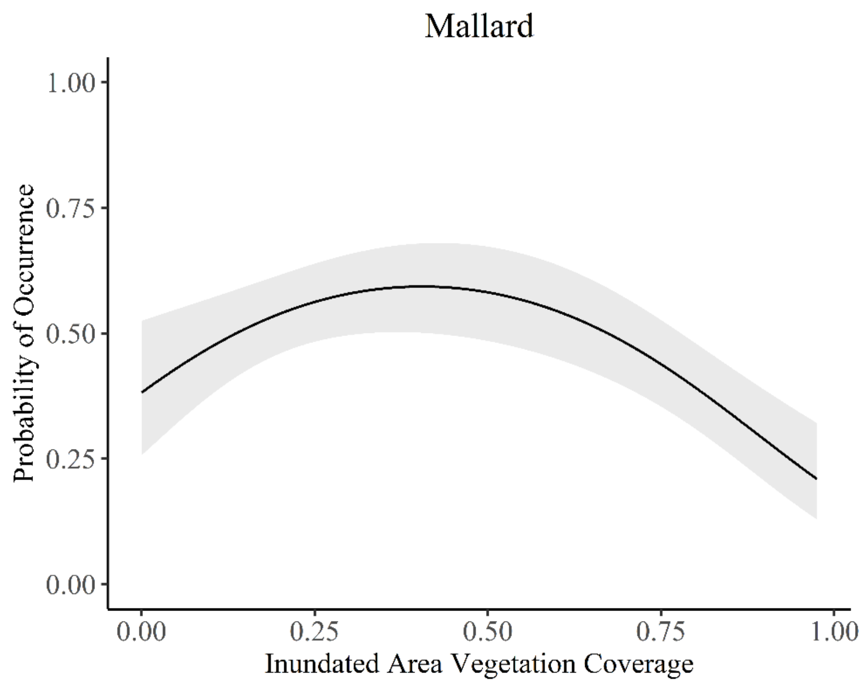

Figure 2.10. Probability of occurrence estimates (85% CI) for mallards relative to the inundated area vegetation coverage proportion during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota.

For northern pintail occurrence, management method was not included in the best fit model (Table 2.3, Appendix A (Table A.9)). The "No Management" model group produced the model with the lowest overall AIC_C score (~87% AIC_C weight, Appendix A (Table A.8)). Higher proportion inundated and larger inundated area increased the probability of northern pintail occurrence (proportion inundated $\hat{\beta} = 0.582$, CI = [0.193, 0.962], inundated area $\hat{\beta} = 0.830$, CI = [0.470, 1.211]). The highest probability of pintail occurrence related to depth was at ~.55 m {depth ($\hat{\beta} = 10.887$, CI = [5.418, 17.507]); depth^2 ($\hat{\beta} = -9.924$, CI = [-17.981, -4.061])} (Appendix A (Table A.9)).

For northern shoveler occurrence, management method was not included in the best fit model (Table 2.3, Appendix A (Table A.9)). The "No Management" model group produced the model with the lowest overall AIC_C score (~84% AIC_C weight, Appendix A (Table A.8)). Inundated area increased the probability of northern shoveler occurrence ($\hat{\beta} = 0.977$, CI = [0.648, 1.335]). The highest probability of occurrence related to inundated area vegetation coverage occurred at ~0.34 vegetation coverage (Figure 2.11){ inundated area vegetation coverage ($\hat{\beta}$ = 0.029, CI = [-0.008, 0.067]); inundated area vegetation coverage^2 ($\hat{\beta}$ = -4.212-04, CI = [-7.871e-04, -6.916e-05])}.

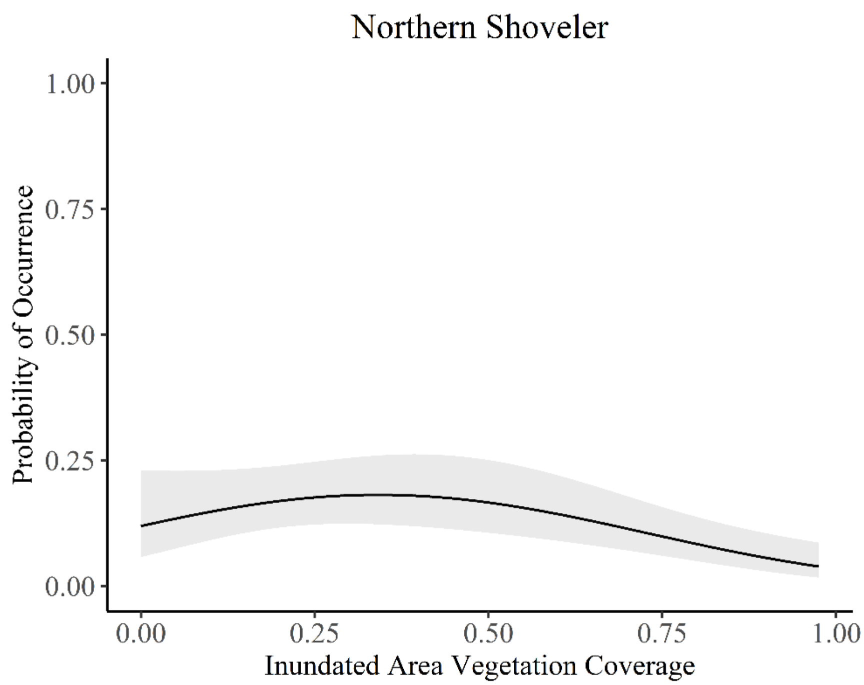

Figure 2.11. Probability of occurrence estimates (85% CI) for northern shovelers relative to the inundated area vegetation coverage proportion during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota.

Duck Density

For "any duck" density, the best fit model (~81% AIC_C weight) was from the "No Management" model group and did not include management method (Appendix A (Table A.10)). Estimated "any duck" hurdle density from harvested wetlands had a CI that overlapped the point estimate from the idled level. Greater proportion inundated increased density($\hat{\beta}$ = 0.426, CI = [0.175, 0.677]), whereas larger inundated area decreased "any duck" truncated density ($\hat{\beta}$ = 0.483, CI = 0.326 – 0.641; Table 2.3, Appendix A (Table A.11)). The highest truncated densities of “any duck” related to water depths occurred at ~0.53 m {depth ($\hat{\beta}$ = 6.703, CI = [4.391, 9.015]); depth^2 ($\hat{\beta}$ = -6.281, CI = [-8.430, -4.132])}. Truncated and hurdle “any duck” densities decreased as inundated area vegetation coverage proportion increased >0.10 (Figure 2.12){inundated area vegetation coverage ($\hat{\beta}$ = -0.591, CI = [-2.249, 1.068]); inundated area vegetation coverage^2 ($\hat{\beta}$ = -0.917, CI = [-2.661, 0.826])}.

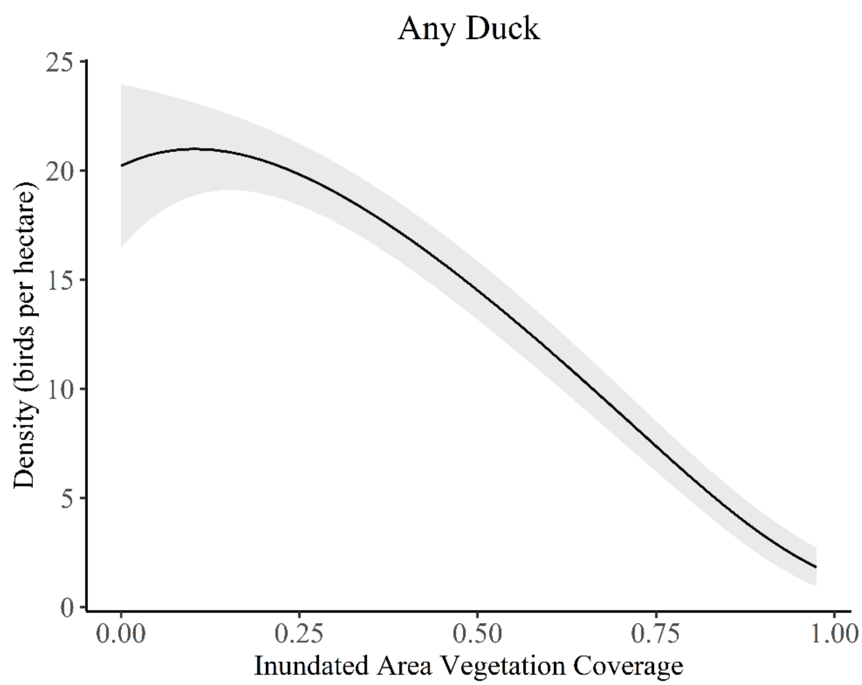

Figure 2.12. Hurdle density estimates for “any duck” relative to the inundated area vegetation coverage proportion during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota.

For blue-winged teal density, the “No Management” model group produced the top model (~98% AIC$_C$ weight, Appendix A (Table A.10)) and did not include management method (Table 2.3, Appendix A (Table A.11)). Increased inundated area and later dates decreased blue-winged teal truncated density (inundated area $\hat{\beta}$ = -0.998, CI = [-1.187, -0.808], date $\hat{\beta}$ = -0.392, CI = [-0.524, -0.260]; Appendix A (Table A.11)). The greatest truncated blue-winged teal density occurred at ~0.14 inundated area vegetation coverage proportion{inundated area vegetation coverage ($\hat{\beta}$ = 0.437, CI = [-1.437, 2.310]); inundated area vegetation coverage^2 ($\hat{\beta}$ = -1.490, CI = [-3.468, 0.489])}. Hurdle density for blue-winged teal was greatest at lower levels of inundated area vegetation coverage (0-0.25) and decreased with inundated area vegetation >0.14 (Figure 2.13).

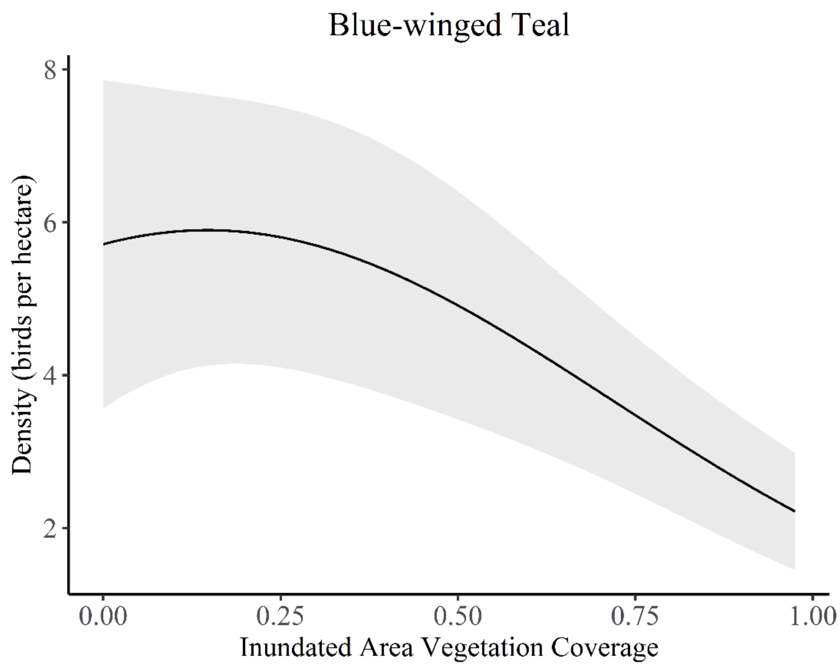

Figure 2.13. Hurdle density estimates (85% CI) for blue-winged teal relative to inundated area vegetation coverage proportion during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota.

For gadwall density, Poisson models were used because there was no indication of overdispersion. The best fit model (~99% AIC_C weight, Appendix A (Table A.10)) came from the "Management" model group. Burned, disked, and mowed wetlands had lower gadwall hurdle densities than idled wetlands (Figure 2.14, Appendix A (Table A.12)). The gadwall hurdle density estimate from harvested wetlands had a CI that overlapped the point estimate from the idled level. Predicted truncated density estimates for gadwall decreased with date ($\hat{\beta}$ = -0.499, CI = [-0.627, -0.371]) and as inundated area increased ($\hat{\beta}$ = -1.198, CI = [-1.349, -1.046]; Table 2.3, Appendix A (Table A.11)).

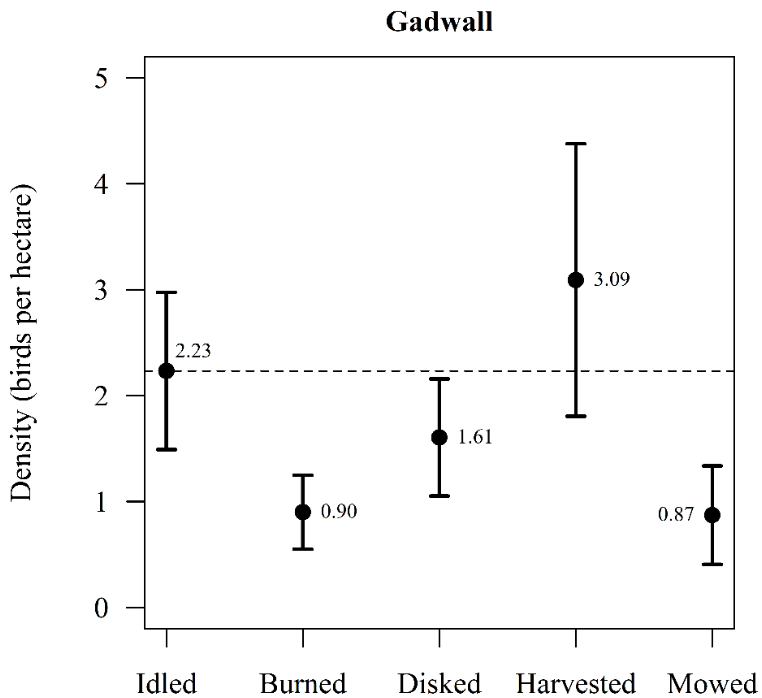

Figure 2.14. Hurdle density estimates (85% CI) of gadwall for each wetland management method during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota. The dashed horizontal line demarcates the idled management level mean estimate.

For mallard density, the best fit model (~95% AIC_C weight, Appendix A (Table A.10)) came from the "No Management" model group and did not include management method (Table 2.3, Appendix A (Table A.11)). Larger inundated area decreased predicted mallard truncated density ($\hat{\beta}$ = -1.108, CI = [-1.287, -0.929]). Truncated mallard density estimates also decreased with increased inundated area vegetation coverage {inundated area vegetation coverage ($\hat{\beta}$ = -1.954, CI = [-3.889, -0.020]); inundated area vegetation coverage^2 ($\hat{\beta}$ = 0.700, CI = [-1.336, 2.737])}. Mallard hurdle density decreased as inundated area vegetation coverage proportion increased >0.09 (Figure 2.15).

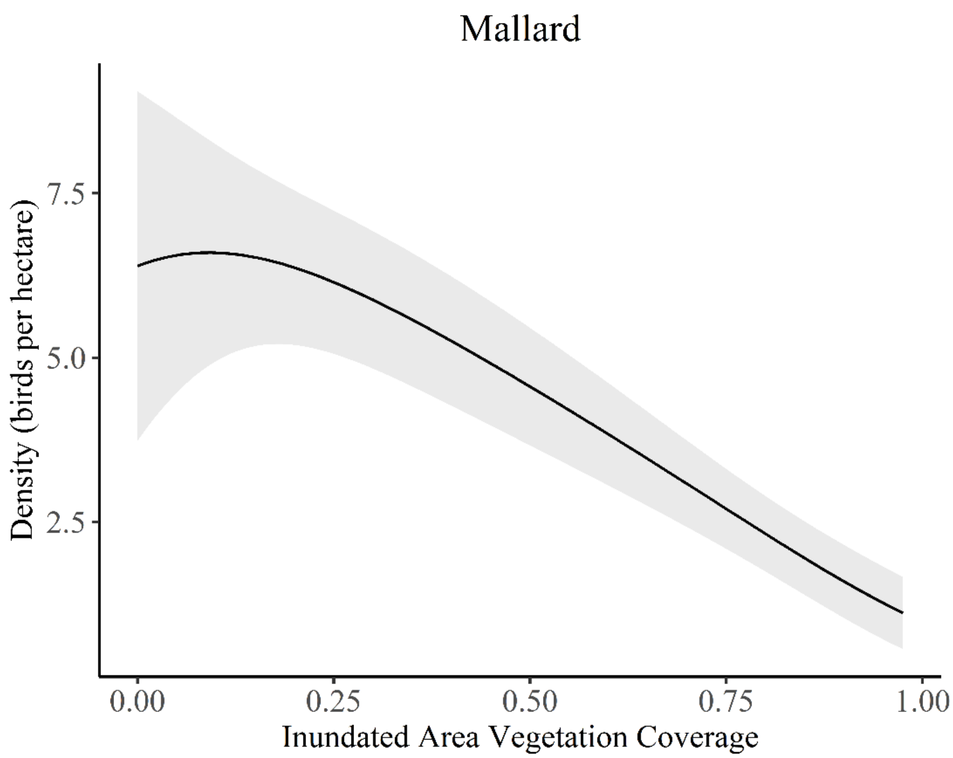

Figure 2.15. Hurdle density estimates (85% CI) for mallards relative to inundated area vegetation coverage proportion during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota.

For northern pintail density, the "No Management" model group supplied the best model (~90% AIC_C weight, Appendix A (Table A.10)) and did not include management method (Table 2.3, Appendix A (Table A.11)). Larger inundated area decreased northern pintail truncated density ($\hat{\beta}$ = -1.240, CI = [-1.687, -0.792]). Truncated pintail density estimates were lowest at ~0.62 inundated area vegetation coverage proportion{inundated area vegetation coverage ($\hat{\beta}$ = -7.476, CI = [-11.240, -3.712]); inundated area vegetation coverage^2 ($\hat{\beta}$ = 6.006, CI = [2.145, 9.867])}. Hurdle density estimates decreased as vegetation coverage increased (Figure 2.16).

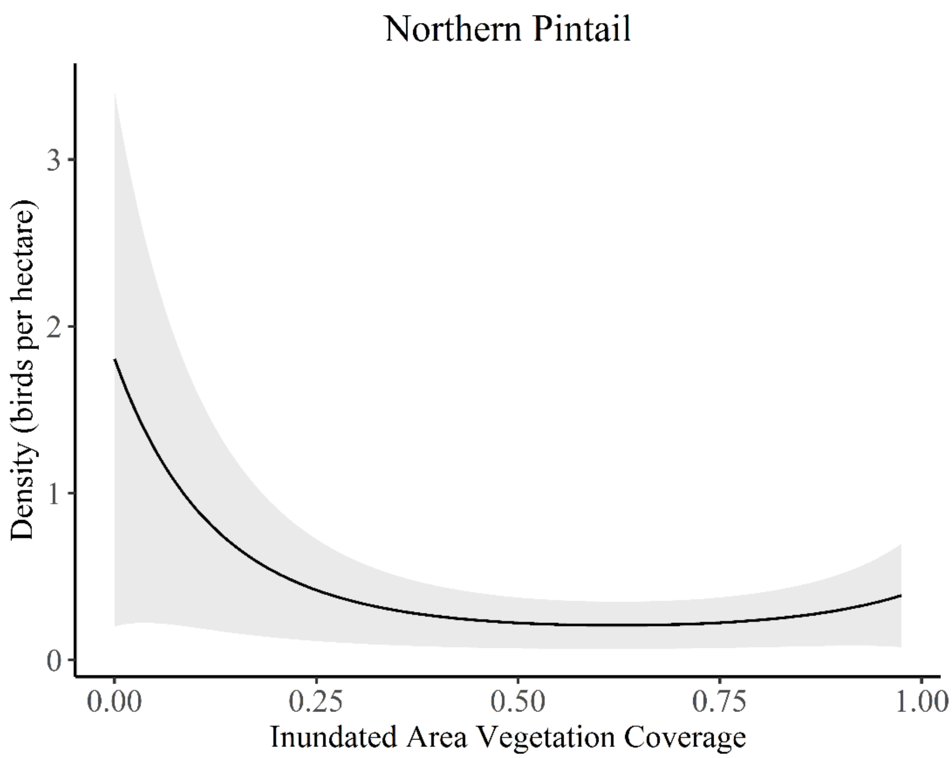

Figure 2.16. Hurdle density estimates for northern pintail relative to inundated area vegetation coverage proportion during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota.

For northern shoveler density, Poisson models were used because there was no indication of overdispersion. The best fit model (~100% AIC_C weight, Appendix A (Table A.10)) came from the "Management" model group. Burned, disked, and harvested wetlands had greater hurdle densities of northern shovelers than idled wetlands (Figure 2.17, Appendix A (Table A.12)). Shoveler density estimates for mowed wetlands had CIs that overlapped the point estimate from the idled level. Larger inundated area decreased northern shoveler truncated density ($\hat{\beta}$ = -0.862, CI = [-1.033, -0.692]; Table 2.3, Appendix A (Table A.11)).

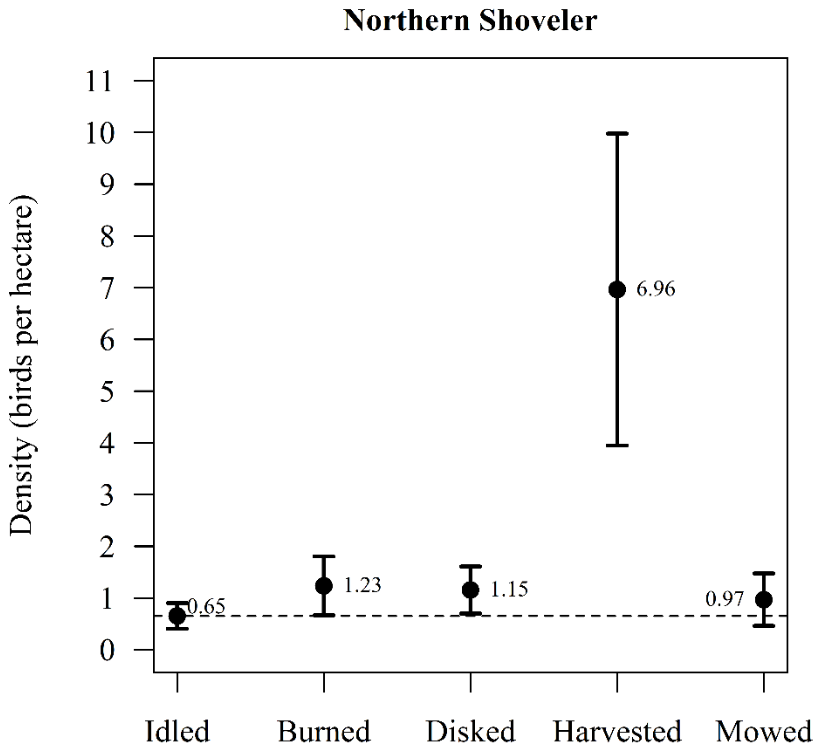

Figure 2.17. Hurdle density estimates (85% CI) of northern shoveler for each wetland management method during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota. The dashed horizontal line demarcates the idled management level mean estimate.

Discussion

Management method and vegetation predictor variables had varying influences on occupancy and density of shorebirds and ducks. Management method directly affected vegetation structure and, for certain species, was a better predictor of occupancy and density than the vegetation metrics evaluated in this study. Management method helped to provide better explanations of variance in occupancy for yellowlegs and "any shorebird" and density for gadwall and northern shovelers. Duck groups that included vegetation coverage instead of management method as a predictor variable displayed higher probability of occurrence in low to medium proportions of inundated area vegetation coverage. However, waterfowl density estimates decreased with increased inundated area vegetation coverage. Therefore, waterfowl densities were higher in agricultural wetlands with lower proportions of vegetation coverage irrespective of the method of the vegetation reduction. Except for killdeer, vegetation coverage or height did not solely influence shorebird occurrence or densities.

Vegetation Response to Management Method

Manipulation techniques (i.e., burned, disked, harvested, mowed) used as standard agricultural practices by farmers produced lower inundated area vegetation heights and coverage in comparison to idled wetlands. Burning and disking manipulations were the most effective at decreasing inundated area and mudflat vegetation heights and coverages. While harvesting wetlands decreased inundated area vegetation coverage more than other manipulations, it also produced the highest comparative mudflat vegetation coverage and height because the post-harvest vegetation was short and easily covered by spring water levels within the lower spots of the wetland. Yet, the vegetation stubble left after harvesting was not inundated on the mudflats. Consequently, mudflats of harvested wetlands had taller exposed vegetation height and greater vegetation coverage. Disked wetlands were the only wetlands with a significantly reduced height of mudflat vegetation as compared to idled wetlands. Mowed wetlands, although having the lowest heights, were typically not followed by a vegetation collecting method (i.e., raking and bailing) and therefore had greater vegetation coverage than other management methods.

Studies on wetland vegetation manipulation techniques, such as burning, grazing, water level manipulation, and herbicide have reported manipulation effects on vegetation and wildlife (Bruggman 2017; Anderson et al. 2019). Bruggman (2017) found that combinations of mowing, chemical applications, and fire management methods for cattail control had varying effects on live cattail. Studies on burning, mowing, grazing, and disking wetlands have concluded that these manipulation techniques reduce biomass and densities, however, these studies were often conducted within grasslands or non-cropland and conducted for experimental purposes (i.e., done with different intensities) rather than a normal agricultural practice (Silver and Vamosi 2012; Anderson et al. 2019). My study was novel with respect to real-world farming practices and its effect on wetland vegetation structure and thus there are few studies for direct comparison.

Wetland management methods have been documented to affect other trophic levels through impacts on vegetation. Wetland manipulations have been used for experimentally altering open water-to-emergent vegetation ratios to examine the effect on invertebrate abundance and species richness and have concluded with mixed results (Kaminski and Prince 1981a; Murkin et al. 1982; Euliss and Mushet 1999). Invertebrate community characteristics may subsequently influence waterbird use of wetlands (Kaminski and Prince 1981a; Murkin and Kadlec 1986; Davis and Smith 1998), because aquatic invertebrates are a primary food source for many waterbirds. Bruggman (2017) reported that vegetation treatments (i.e., burning, chemical application, or fire) had little effect on overall bird or amphibian species richness despite various species-specific effects on abundances. Yet, the literature was unclear if the resulting vegetation structure or the invertebrate numbers were the causal factor for use by waterbirds.

Shorebird Occurrence and Density

Management method was an important factor in the probability of occurrence for yellowlegs and “any shorebird” within agricultural wetlands in the Drift Prairie of North and South Dakota. Agricultural manipulation of wetlands resulted in sparsely vegetated (i.e., lower densities and heights than idled wetlands) areas which have been shown by other studies as important to shorebirds (Skagen and Knopf 1994b; Davis and Smith 1998; Skagen et al. 1999). Results indicated that management method explained more variation in species occurrence than resulting vegetation structure to “any shorebird” and yellowlegs. Killdeer models were the only shorebird model group to include any vegetation variables in a final model. The low frequency at which the vegetation variables were included in any of the shorebird final models, suggests two potential explanations. First, management method, in addition to decreasing wetland vegetation heights and vegetation coverages, may have affected characteristics of agricultural wetlands not measured or accounted for in this study that were important to shorebirds or second, vegetation variables measured in this study were not useful metrics for describing wetland use by shorebirds. The first explanation may be more likely because vegetation heights and densities have been shown to affect shorebird occurrence and abundance in other studies. Many shorebird studies indicate that shorebirds use less vegetated mudflats and shallow water habitats (Skagen and Knopf 1994b; Davis and Smith 1998; Skagen et al. 1999; Stutzman and Fontaine 2015).

The lack of model fit for “any shorebird” and yellowlegs densities, may be related to the difficulty of modeling migratory species, especially shorebirds, which use a temporally changing landscape and may be influenced by social behavior and distribution of resources on the landscape (Folmer et al. 2010; Albanese et al. 2012). The final density models for killdeer and sandpipers included a landscape level effect of the surrounding number of wetlands which supports the hypothesis that shorebirds utilize novel habitat and locate habitat opportunistically. Consequently, modeling shorebird densities may be difficult without a larger sample of wetlands (Albanese et al. 2012).

Harvested wetlands had the highest occurrence probabilities of the management method categories for “any shorebird” and yellowlegs. Harvested wetlands left behind standing crop stubble, crop litter discarded from harvesters, and waste grain. These remnants of harvesting may be similar to residual litter left by wetland plants after other manipulations techniques (e.g., mowing) which have been shown to increase aquatic invertebrate abundances (Kaminski and Prince 1981a; Murkin et al. 1982; Gray et al. 1985) and diversity (Christensen and Crumpton 2010) and thus, shorebirds may be cuing in on residual vegetation structure of harvested wetlands as an indicator of foraging quality (Stutzman and Fontaine 2015). For potentially similar reasons, mowed wetlands increased probability of occurrence for “any shorebird”. Another possible explanation for higher use of harvested wetlands might be that density and height of harvested crops was preferred to wetland vegetation that is more typical in agricultural wetlands.

Burned wetlands, which had the second lowest inundated area vegetation coverage estimate of the management method categories, were important positive factors for occurrence of yellowlegs but were indistinguishable (i.e., CI that overlapped the point estimate of the idled level) from idled for “any shorebird” occurrence. De Szalay and Resh (1997) found that burning wetlands was correlated with higher abundances of certain aquatic invertebrates, which possibly contributed to its influence on yellowlegs in this study. Similarly, Davis and Bidwell (2008), found that invertebrate richness and diversity did not differ greatly between wetlands manipulated with different methods within agricultural lands, but grazed, mowed, and burned wetlands were associated with higher biomass of certain invertebrate taxa. They also found that richness and diversity were highest in grazed wetlands and lowest in disked wetlands which might explain why disked wetlands in this study were either indistinguishable from or similar to idled wetlands for probability of occurrences for the shorebird groups that included management method in the final model. However, this study did not have the invertebrate data to assess its effects directly.

Other wetland related factors which influenced multiple shorebird groups were inundated area and near-shore depth complexity. Increases in size of the inundated area increased the probability of occurrence for all shorebird groups and decreased the density estimates for sandpipers and killdeer. Inundated area was not included in the final models for the other shorebird group densities, but often has a similar effect on densities of other bird species (Colwell and Taft 2000). Variation in near-shore water depths increased the probability of occurrence for "any shorebird" and yellowlegs as well as density for sandpipers. Wetlands that have a variety of near-shore water depths can accommodate multiple guilds of shorebirds with different foraging methods and body sizes. Mudflat characteristics (i.e., distance, vegetation height, and vegetation coverage) did not seem to have a pronounced effect on any of the shorebird models unlike other studies which linked more mudflat area to increased shorebird utilization (Skagen and Knopf 1994b; Davis and Smith 1998). Farmers often disk and plant as much wetland area as possible and thus, the surrounding agricultural uplands generally have similar, barren characteristics in the spring. Therefore, large mudflat areas may not be a major wetland selection factor for shorebirds in an agricultural setting, or the variation of mudflat measurements in this study was too low to discern a difference in shorebird occurrence or density. If this is the case, then wetland selection by shorebirds in an agricultural field may be more dependent on the inundated area vegetation structure that, when manipulated, provides more of an unobstructed view similar to what is common in the mudflat vegetation structure.

Manipulated agricultural wetlands may provide the visual cue of a desired wetland for shorebirds, but as Euliss and Mushet (1999) found, agricultural wetlands had fewer and less diverse invertebrate communities compared to wetlands in more natural landscapes. Yet, shorebirds have been shown to prefer agriculture fields to more natural wetlands (Twedt et al.

1998; Taft and Haig 2005; Niemuth et al. 2006; Stutzman 2012; Stutzman and Fontaine 2015). Consequently, a selected habitat that is lower quality (i.e., lower invertebrate numbers) than other available habitats and reduces survival may be considered an ecological trap (Battin 2004). However, it may be difficult to study the causal relationship of an ecological trap (Donovan and Thompson III 2001; Hale and Swearer 2016) to determine whether agricultural wetland habitat leads to poorer shorebird body condition that could ultimately influence survival or reproductive success (Tulp et al. 2009; Gibson et al. 2018; Swift et al. 2020).

Duck Occurrence and Density

Management method was not an important factor predicting occurrence for any of the duck groups in this study. However, dabbling ducks had a higher probability of occurrence in low to medium inundated area vegetation coverage regardless of method of vegetation reduction. All waterfowl group occurrence models, except northern pintail and blue-winged teal, included inundated area vegetation coverage in the final models. The inclusion of inundated area vegetation coverage instead of management method in the final models suggests management method was likely only affecting occurrence of waterfowl in agricultural wetlands through the reduction of vegetation coverage.

Other studies found that wetlands in the “hemi-marsh” (roughly 50:50 open water to emergent vegetation) phase were correlated with higher use by and abundances of waterfowl (Weller and Spatcher 1965; Weller and Fredrickson 1973; Murkin et al. 1982; Smith et al. 2004; Pearse et al. 2011). My study suggests that agricultural wetlands with low to medium proportions of inundated area vegetation coverage were correlated with higher probabilities of occurrence for most waterfowl groups. A more open wetland vegetation structure rather than a hemi-marsh may have been beneficial for predator detection or social interactions in a cropland setting.

Probability of occurrence increased with the size of inundated area for all waterfowl groups, except gadwall which did not include inundated area as a predictor variable in its final model. This result was similar to many other studies which positively associated wetland size with abundance and diversity of waterfowl and waterbirds (Lokemoen 1973; VanRees-Siewert and Dinsmore 1996; Krapu et al. 1997; Colwell and Taft 2000). Larger wetlands have more area to support individuals and likely have more cover for escape and seclusion from conspecific mate competition during courtship. In this study, depth was also important for occurrence of blue-winged teal and pintails. Wetland depth is often a factor in occurrence and abundances of waterfowl, but may differentially effect species (DuBowy 1988; Colwell and Taft 2000; Isola et al. 2000).

Management method was an important factor in gadwall and northern shoveler density models. The gadwall models showed lower estimated densities for burned, disked, and mowed manipulations as compared to the idled level. Though all manipulations decreased inundated area vegetation heights and densities, burned, disked, and mowed manipulations may have had side effects that did not impart as good of a resource as harvested wetlands (i.e., grain waste) did for gadwall. Interestingly, northern shovelers had opposite associations compared to gadwalls for management method levels with burned, disked, and mowed wetlands having increased density estimates compared to idled wetlands. Harvested wetlands increased density for gadwall and shovelers but was only distinguishable from idled wetlands for shovelers. Further, shoveler density was higher on harvested wetlands, but only two of 10 harvested wetlands had a non-zero count of shovelers. Kastner et al. (2016) found that wetlands that were part of shoveler habitat were often within, or in close proximity to, agricultural fields. Higher densities of shovelers, which are animal food specialists (Euliss et al. 1997), might indicate that harvested wetlands provided better habitat than other types of manipulated wetlands for invertebrates species that are preferred by shovelers. Their reliance upon invertebrates for forage could have made it more probable for them to congregated where aquatic invertebrates were more abundant, diverse, or nutritionally satisfying (Kaminski and Prince 1981b), but invertebrate sampling would be needed to examine this hypothesis. More harvested wetlands would also need to be surveyed to confirm if they do attract higher densities of northern shovelers than other wetland management methods or if this was an artifact of a small sample size for this management level.

This study could have been improved with increased sampling of harvested and mowed wetlands. Increases in those response categories would have helped to narrow confidence intervals and improve overall models. However, water dynamics in the PPR that would allow for a wetland to be classified as "harvested" may occur infrequently. The sequential steps would include preparation for planting (manipulation), planting, harvesting, either the choice of not disking or the inability to disk a wetland after harvest, and then water levels high enough to pond water the next spring. The first three steps would require little or no ponded water in the wetland. Another potential oddity was that mowed wetlands in this study did not have the cut vegetation removed after cutting. It is unknown if this was because water dynamics disallowing for vegetation gathering and removal or if leaving the vegetation was a common agricultural practice.

Implications for Conservation

The results of this study can inform farmers and organizations which work with farmers about how waterfowl and shorebirds use wetlands within crop fields in the Drift Prairie. Many conservation programs have been implemented and supported by federal, state, and non-governmental agencies and are aimed at improving water quality, soil quality, soil erosion, wildlife habitat, and habitat preservation on private lands. Some of the programs target working lands such as cropland or pastureland with the added goal of improving profitability or benefits to landowners or operators. Certain programs also target wetlands within cropland to improve and protect temporary and seasonal wetlands that may have value to wildlife in general and migratory birds in particular. Additionally, cropland conservation programs try to improve the soils by planting cover crops, planting appropriate wetland plants, planting salt-tolerant crops in saline soils, or installing fencing to allow livestock to graze residual crop or cover crop vegetation. Stipulations exist regarding size, length of enrollment, and agricultural practices allowed within the enrolled areas. Allowed practices may include combinations of continued cultivation, haying, or grazing of the enrolled land.

I determined that migratory shorebirds and dabbling ducks were generally found with greater frequency and density in less vegetated wetlands and often had greater probabilities of occurrence and densities in harvested wetlands. Thus, a working lands wetlands program that would potentially allow for vegetation manipulation and seed or grain waste to occur could benefit migratory waterbirds. A conservation program that encouraged planting of appropriate seed mixes and vegetation manipulations such as grazing, haying, or harvesting within agricultural wetlands may improve both invertebrate metrics (de Szalay and Resh 1997; Davis and Bidwell 2008) and provide supplemental seed or grain waste to migratory birds. Current programs that prohibit any manipulations (e.g., burning, grazing, mowing, haying) within the wetlands located in cropland may not attract as many waterfowl or shorebirds as they could if wetlands are overgrown and choked with vegetation. Migrating waterfowl and shorebird occurrences and densities would likely decrease if a wetland became overgrown with vegetation, which could occur within unmanipulated temporary and seasonal wetlands in croplands of the Drift Prairie of North Dakota and South Dakota.

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CHAPTER 3. PROFITABILITY OF PLANTING CORN AND SOYBEANS IN WETLANDS AND OTHER LOW SPOTS IN SOUTHEASTERN NORTH DAKOTA

Abstract

Commodity prices, land values, and government policy have motivated farmers to increase the amount of land they have in crop production. Some of the expansion occurred in temporary and seasonal wetlands within crop fields that were cultivated when water conditions allowed. I examined proportions of wetland-related landforms that were cultivated, and estimated yield and profit obtained from the cultivated portions of those landforms to help achieve beneficial outcomes for farmers and society. My results suggest that about half the area of temporary wetlands and nearly a third of the area of seasonal wetlands are cultivated annually on average in crop fields. This level of cultivation equates to an average of between 0.54–0.85 hectares planted in each temporary and seasonal wetland, with a slightly larger area planted for soybeans than corn, which is likely related to later planting and shorter maturity dates. Corn yield estimates were on average 12% less in cultivated portions of temporary (8.7 Mg/ha CI = [8.5, 9.0]), and 23% less in seasonal wetlands (7.6 Mg/ha CI = [7.3, 7.8]) compared to upland areas (9.9 Mg/ha CI = [9.7–10.2]). Soybeans were similar in yield for cultivated portions of temporary wetlands (2.6 Mg/ha CI = [2.5–2.6]) compared to upland areas (2.5 Mg/ha CI = [2.5–2.6]), whereas cultivated portions of seasonal wetlands averaged a 4% reduction in soybean yields (2.4 Mg/ha CI = [2.3–2.4]). Corn profit estimates from cultivated portions of temporary ($557/ha (CI = [$513, $602]) and seasonal wetlands ($449/ha (CI = [$405, $493]) were on average 28% and 42% lower than upland estimates ($776/ha CI = [$734, $817]), respectively. Soybean profit estimates from cultivated portions of temporary ($490/ha (CI = [$463, $518]) and seasonal wetlands ($420/ha (CI = [$392, $448]) were on average 10% and 23% lower than

upland estimates ($544/ha CI = [$518, $571]), respectively. These results may help farmers identify areas in their fields where they can improve profitability through alternative land management practices or by enrolling consistently less profitable portions of their fields in conservation programs.

Introduction

Many farmers are motivated to cultivate as much land as they can effectively manage. In North Dakota, there has been an increase in the amount of land in agricultural production over the past 50 years because of commodity prices, land values, and government programs and policies (Lark et al. 2015; Brandes et al. 2016). It is estimated that planted corn and soybean land area tripled from 1980–2011 in North Dakota and South Dakota (Johnston 2014). This rapid cropland expansion has resulted in the conversion of agriculturally less productive land (e.g., low spots and wetlands) and grasslands into agricultural production (Lark et al. 2015; Lark et al. 2020). A threefold increase in corn and soybean prices occurred during 2002–2012 and likely contributed to the increase in wetland conversions (Johnston 2013) and to 55,000 hectares (ha) of wetlands being incorporated into cropland production from 2008–2012 in North Dakota, South Dakota, and Minnesota (Lark et al. 2015). Yet, little is known about how much actual cultivated area small wetlands regularly provide or how they contribute to yield and profit of farming operations. Insights to agricultural wetlands metrics may help to provide guidance for alternative management practices to increase overall farm profitability.

Wetlands of the Prairie Pothole Region (PPR), a physiographic region spanning across portions of Iowa, Minnesota, North Dakota, South Dakota, and Canada, are classified by hydroperiod and exist on a hydrological continuum influenced by atmospheric and underground water dynamics (Stewart and Kantrud 1971; Euliss et al. 2004; Hayashi et al. 2016). More than

80% of remaining temporary and seasonal wetlands in North Dakota's Drift Prairie, a physiographic region within the PPR, are located within annual crop or alfalfa fields (Niemuth et al. 2006); hereafter I will refer to these wetlands as agricultural wetlands (AW). Frequently AW are cultivated, a process of manipulating them in preparation for planting a crop, planting a crop, or harvesting crop. Agricultural wetlands that have not been drained or filled are cultivated regularly, (e.g., temporary wetlands) or periodically (e.g., seasonal and semi-permanent wetlands) when conditions are dry enough to operate machinery within them. Temporary and seasonal AW can often be disked in the late fall when wetlands are dry, but many times water dynamics in the spring may prevent or delay crop production.

Much of the success growing, harvesting, and profiting from cultivating crops within an AW is determined by timing and magnitude of precipitation events. The unpredictability of winter and spring precipitation events results in greater economic uncertainty when cultivating within AW than in the surrounding uplands because of the capability of wetlands to pond water. Economic losses may occur during any part of cultivating AWs, but financial and yield losses are of greater magnitude when a crop has been planted and plants are killed following a precipitation event that causes ponded water for an extended time (DeBoer and Ritter 1970; Lizaso and Ritchie 1997; Sullivan et al. 2001; Zaidi et al. 2004). The increase in financial loss is greater because seed costs can be one of the most expensive direct input costs on a per acre basis (Swenson and Haugen 2021). Two or more days of ponded water over a planted crop can result in a yield reduction or complete loss of the crop (i.e., drown-out with no crop yield) within the ponded water area (Wenkert et al. 1981; Rhine et al. 2010; Bailey-Serres et al. 2012). Potential losses are further increased if a drown-out occurs after other inputs (e.g., fertilizer, fungicide, herbicide, etc.) have been applied to an already planted crop.

Many farmers across the Drift Prairie continue to cultivate AW despite financial risk (Fey et al. 2016; Clare et al. 2021). There are multiple reasons why farmers continue this practice such as trying to reduce compaction of soils when driving around wetlands, the ease of driving through rather than around, the potential income from cultivating additional acres (assuming a successful AW crop), or the potential to insure the planted area to protect against crop loss (Cortus et al. 2011). Profit (i.e., revenue minus input costs) seeking has been shown to influence other farming management decisions (Arbuckle 2015; Plastina et al. 2020) and may be a reason farmers continue cultivating AW. Regardless of the reason, estimates of how often and how much area of temporary and seasonal wetlands are cultivated across multiple years in the Drift Prairie may help farmers make more informed management decisions and help inform conservation programs to enhance ecosystem service of wetlands.

The ability to assess both yield and profitability at fine resolutions (~ 20-30 m^2) within a field has been facilitated by precision agriculture (PA) technologies. PA technologies have allowed farmers to track inputs (e.g., seeding rates, fertilizer rates, etc.) and crop yields at a fine resolution using machinery-integrated global positioning systems (Muth 2014; Brandes et al. 2016; Fey et al. 2016; Schimmelpfennig 2016). The goal of PA is to increase profitability by allowing producers to optimize management practices at the sub-field level (Lerch et al. 2005; Schimmelpfennig 2016; Long et al. 2016; Lindblom et al. 2017; Paustian and Theuvsen 2017). While this technology has impressive capabilities, it requires time and effort to use effectively, as well as new skill sets of producers such as data stewardship, spatial data processing, and sensor calibrations. As a result, farmers often only view yield monitors and yield maps to get a general sense of or average of their yield for the current harvest and may not aggregate years of their input and harvest data to thoroughly examine their sub-field operations (Lachia et al. 2021), which could help to assess the profitability of farming marginal lands such as AW (Clare et al. 2021).

Two studies have recently examined subfield level profitability of AW in the PPR of Iowa (Fey et al. 2016) and Canada (Clare et al. 2021) and determined there was a higher frequency of economic losses when cultivating within wetlands than in the adjacent upland areas. Clare et al. (2021) also reported that many of the farmers underestimated the magnitude of the loss in wetland areas. These studies spotlight the problems farmers experience when attempting to farm wetland or low spot areas but were conducted under different climatic and policy variables. Therefore, to gain understanding of these processes in North Dakota, I compared profit and yield for landform features, such as wetlands and land immediately around wetlands, to the surrounding land within crop fields. I also examined planting metrics for landform features within fields, such as the proportion of each landform that was planted and the number of hectares of each landform planted. These planting metrics may help further understand how much and how frequently farmers cultivate wetland related landform features and how it contributes to farming operations in a long time series of data encompassing various climatic conditions.

Methods

Study Area

The PA data in this study came from corn-soybean rotational cropping systems, which is common in the Drift Prairie of southeastern North Dakota. Prior to European settlement, the PPR was a vast grassland interspersed with depressional wetlands. In the Drift Prairie, the highest wetland densities can reach >57/km^2 (Dahl 2014), mainly composed of temporary and seasonal wetlands. Most wetlands are <0.5 ha in area but can reach sizes of >40 ha for permanent bodies of water (Kantrud et al. 1989; Batt 1996; Niemuth et al. 2010). However, the gently rolling landscape made the Drift Prairie conducive to cultivation and thus land use was predominantly agriculture. During 2017, 73% of land from counties fully residing within the Drift Prairie of North Dakota was designated as cropland (NASS 2017).

Annual precipitation in North Dakota typically ranged from 40.6 cm (16 inches) in the northwest to about 60 cm (24 inches) in the southeast. The wettest consecutive 5-year period since 1900 was from 2007–2011 (Frankson et al. 2022). July temperatures in North Dakota range from 18.3–22.2°C (65–72°F).

Field Data

I acquired precision agriculture data from four farmers. These data included planting and harvesting data for most crop fields and years. Field-year is designated as the unique combination of a crop field in each year because there were different crops and environmental conditions resulting in different extents of crop fields in each year and therefore, data were not available in all years for every field. Field data was missing for various reasons, some of which included crops other than corn or soybeans were planted in the field or the farmer did not provide the data. The PA data type available for a crop field had the potential to change from year to year. PA data were collected by different makes, models, and types (e.g., combine harvesters, planter) of machinery and software, but each point had location information associated with other data such as the name of the crop field (assigned by farmers), date, crop type, seeding rate, yield obtained, moisture content, product flow rates, or grain mass. I aligned common ancillary data into a common system and converted it to geospatial point format (e.g., point shapefile) for further manipulations and visualizations.

Harvest Data

Harvest data collected from combine harvesters (i.e., farm machinery which reaped, threshed, gathered, and winnowed grain crops) periodically contains errors in yield estimates for various reasons; most commonly they are attributed to partial swaths of grain into the header of the harvester, time lag of grain from collection to grain flow sensors, geo-positional errors, surging grain through the system, rapid velocity changes of the harvester, grain loss, and sensor accuracy (Blackmore and Marshall 2003). These errors pose challenges for mapping and accurate inference, so various procedures are typically used to flag, filter and smooth the data (Thylén et al. 2000; Blackmore and Marshall 2003; Sudduth and Drummond 2007). Existing methods had the potential to bias data, so I modified some of the standard methods used by the agriculture industry.

Yield Editor 2.0 (YE2) (Sudduth et al. 2012) software was used to clean the yield errors. Sudduth et al. (2012) explored the options available to flag/filter data points, provided best practices to use the YE2 software, and provided explanations of the calculations used to set filter limits. I used program R (R Core Team 2020) to convert spatial data into YE2-readable text files, write YE2 settings files and batch files, and run the batch files which programmatically started and sent data into YE2 for each field-year yield file. I used settings files to specify which errors to flag and to select the "automated yield cleaning expert" (AYCE) mode which automatically chose flag limits or criteria for the data based on internal evaluations. Some of the limits flagged were minimum and maximum speed, minimum and maximum yield, minimum and maximum velocity, optimal grain flow corrections, optimal moisture corrections, local standard deviation errors, and others. I exported the YE2-processed field-year yield data to comma separated value (csv) files which included a code column that corresponded to the reason or reasons why each line of the data was flagged or not flagged as an error. Often YE2 users will remove data points flagged for being below a certain yield level assuming they are in error, however, these may be accurate data points and without other reasons (i.e., being flagged by additional AYCE codes), these data were considered accurate and used in further analysis. Removing data points solely for low yields may have biased these data and inhibited the ability to examine the low yield areas within a field and thus I removed all flagged data except data points which were flagged solely because of low yield.

I converted cleaned yield csv files back into geospatial point format using program R (R Core Team 2020). I then used ArcGIS v10.5.1 (ESRI 2019) to create a Model Builder (MB) workflow to automate interpolation of the yield data. The cleaned yield spatial point data were interpolated using ordinary kriging with a spherical semivariogram model, 2-m cell size for the output raster, and a variable search radius of 12 points or 25 m to create a raster for each field-year of available spatial data. Each cell value in the rasters contained the interpolated yield estimate. I masked (i.e., bounded) interpolated yield raster for each field-year with a polygon resulting from aggregating and buffering (e.g., by approximately half of the machinery width) the original field-year's harvest spatial point data into a polygon with a 15-m aggregation distance. The mask polygon helped to exclude interpolation through areas where wider than normal gaps in the harvest data existed (e.g., driving around wetlands or other obstacles, or areas where the machinery did not record data).

Planting Data

Planting data was generally less prone to the number and type of errors than that of harvest data. These data were typically analysis-ready or were completely missing which occurred for 11% of field-years in this study. Some planting data had the correct spatial coverage but were lacking the rate of seeds applied to the field. Two of the three farmers that provided planting data used variable rated (VR) planting machinery for all years and the third farmer used VR planting in the last three of 15 years of data provided. Map-based (VR) technologies allow farmers to upload prescription maps into their machinery that contain farmer-defined subsections of fields where different programmed rates of products (i.e., seed, fertilizer, etc.) may be automatically adjusted and applied in the pre-defined area (Grisso et al. 2011). When VR planting was used by a farmer (known through personal communication) but the applied rate was not recorded for all the points in planting, I either substituted a targeted yield rate (i.e., the intended rate of seeds planted) from a nearby crop field of the same crop type and year as a rate for the whole field; or if a prescription map was available for the field in that year, I used the targeted rates from that prescription map for the corresponding subsections of the field. The targeted rates were determined by farmers and were the desired amount of seeds to apply in a specific section of the field by the machinery. The data from the planting showed that machinery rarely planted the exact targeted rate of seeds (e.g., 28,000 seeds per acre) and usually applied slightly too few or too many (e.g., 27,876 seeds per acre) seeds but recorded the actual amount of seeds planted for each data point. I processed planting shapefiles through a similar (i.e., buffer adjusted for machinery width) ArcGIS MB interpolation workflow as the harvest data which generated raster files with the applied seed rate as the cell values.

Fertilizer and Chemical Application Data

Fertilizer and chemical (i.e., herbicide, fungicide, etc.) applications recorded data similar to planting data in that they had targeted rates and applied rates associated with each data point. However, the data for fertilizer and chemical applications from farmers were often unorganized and unreliable and therefore were not used in any analyses. I used North Dakota State University

(NDSU) crop budget estimates in lieu of farmer supplied chemical and fertilizer data (described below).

General Adjustments to Precision Agriculture Data

There were instances where a field-year's planting and harvest data did not completely align because of missing or incomplete data. Visual examination of spatial data helped to determine if the missing data was purposely excluded (i.e., avoided wetland) or a recording error (i.e., missing rows across whole field). Often spatial data errors or machinery errors were displayed as straight line or row pattern (i.e., un-natural boundaries), whereas obstacle purposefully avoided had curved or angled spatial data segments that were congruous with the surrounding spatial data. I clipped planting spatial data to the layout of the harvest spatial data and discarded if, and where, the data were deemed to be recording errors, but were left intact if the differences were determined to be purposefully driven around as would be the case from avoiding a wetland with the machinery. One farmer frequently used multiple combine harvesters in the same field-year but did not collect all the data from each harvester, which left a random coverage of harvest information over the field. I processed these data in the following sequential steps: created a spatial polygon boundary by aggregating the harvest spatial point data with a 30m aggregation distance, then buffered the polygon to account for machinery width, and finally converted "holes" within the polygon that were less than three acres to part of the spatial polygon (i.e., Eliminate Polygon Part tool which made the holes become part of the polygon). I assumed areas larger than 1.2 ha to be recording errors. I used the resulting spatial polygon boundary for the boundary of the field for further harvest data processing.

Wetland Data

The National Wetlands Inventory (NWI) Database (USFWS 2018) was a readily available collection of digitized wetland polygons within the United States. This data layer contained many of the temporary and seasonal wetland areas that were present within the crop fields in this study. For temporary and seasonal wetlands within study crop fields, I converted the supplied vector data to raster data with a 2-m cell size and wetland type as the cell value. The NWI wetland boundaries were static across the years of this study.

I also created a distance-from-wetland (DFW) raster layer, which classified raster cells by Euclidean distance to the nearest wetland into one of the following classes: dist10 (0–10 m), dist20 (10–20 m), and dist30 (20–30 m). Distance categories were multiples of the approximate width of machinery (10 m) which could have influenced farmers' navigation decisions. Also, cropland adjacent to wetlands within the PPR frequently have high soil salinity which may limit crop growth surrounding some wetlands (Seelig 2000; Franzen 2003).

Digital Elevation Models and Sinks

I acquired LiDAR-derived digital elevation model (DEM, https://lidar.swc.nd.gov/) raster data for every crop field in this study. The DEM had a vertical accuracy of ≤15.0 cm root-mean-square error (RMSE) and a horizontal accuracy of ≤1 m RMSE.

Many of the low spots within the crop fields of this study were delineated by the NWI wetlands data; however, I identified additional areas of relative lower elevation across fields, which were not in the NWI database and could potentially pond water and impact crop yields and profitability. To identify low spots, I used ArcGIS to mosaic (i.e., combine) overlapping DEM rasters together and clipped them with the boundary of each corresponding crop field. I processed the clipped rasters through a workflow to create spatial rasters that identified areas where low spots (i.e., sinks) occurred within the field. I defined sinks as a raster cell or cluster of cells that were lower in elevation than surrounding cells and had an undefined drainage direction. I created a "filled" raster through a process called filling where the cell elevations from the DEM were virtually raised until the raster cell would no longer pond water, i.e., the elevation of the cell was raised equal to the lowest elevation of an immediate neighbor (Planchon and Darboux 2002; McCauley and Anteau 2014). I then subtracted the original DEM from the filled raster which produced a sink raster (i.e., producing a raster with the depth of the sinks for each cell) (McCauley and Anteau 2014). The sink rasters were reclassified based on the depth assigned to each cell into the following classes: Sink1 (0–0.15 m), Sink2 (0.15–0.25 m), and Sink3 (>0.25 m). I chose the first interval to correspond with the vertical accuracy of the DEM. The result of this raster created many small (e.g., 1–4 cells) groups of raster cells displaying >0 m filled depth. I then used four repetitions of the "Majority Filter" tool in ArcGIS as a method to smooth and remove small clusters of >0 m depth cells. This process replaces cells in a raster based on the majority of its contiguous neighboring cells. Next, the raster was converted to polygons to be aggregated, spatially combined (i.e., union), and dissolved into a contiguous spatial polygon outlining the sink area. I then used these polygons to clip the "filled" raster (i.e., raster created right after the filling process). The resulting raster contained the raw (unclassified) depth values for each 1 m cell in the sink areas. I classified sink depth again into the Sink1, Sink2, and Sink3 category. Areas outside of the sink raster area was reclassified as 0 m depths. Sink raster layers were static across years.

Landform Designation

I designated landform as a category to classify geospatial data points into specific land features that may affect crop yields and, in turn, profits for farmers. There was a hierarchal categorizing structure because some points may have been geospatially positioned in more than one landform class. For example, a point may have been geospatially located within a sink (e.g., Sink1) and a NWI wetland (e.g., temporary wetland). To address multiple classifications, I categorized each point into a class level from one of eight classes in the following order: NWI wetland class (temporary, seasonal), DFW class (dist10, dist20, dist30), and sink class (Sink1, Sink2, Sink3). The former classes of this category took precedence over the latter. I designated spatial points not identified in any of the previously defined classes as "upland" in the landform category.

Sampling Grid and Raster Extraction

I created a 2 m by 2 m sampling grid using the "Create Fishnet" tool in ArcGIS, which created a point layer over the extent of each crop field. For every field-year, I used the "extract" function in the "raster" package (Hijmans 2020) in program R (R Core Team 2020) which pulled raster data at each point in the sampling grid from each raster layer available for that field-year into a single line of data (i.e., spreadsheet or tabular format). The grid point locations were maintained to sample the same locations across years. Each grid point had the potential of the following data associated to it: crop type, year, field name, farmer identification, yield, seeds applied, sink depth, NWI wetland type, and distance from NWI wetland. I designated empty cells in rasters with an "NA" to distinguish between "no data" values and "0" and therefore each grid point had an "NA" extracted from a raster layer if there was not data associated to that grid point location. However, yield was changed from "NA" to "0" for grid points which had non-empty planting rates (i.e., not missing or non-"NA" from the planting raster) and also had missing yield rates (i.e., "NA" from the yield raster). This was needed in circumstances where an area was planted but had no harvest data because the location was driven around because of a lack of harvestable crop or water obstacle.

Farm Budgets

Some farmers provided financial data, such as seed costs, but most did not provide adequate financial data to allow a complete assessment of profitability. To estimate input costs and selling prices, I used farm budgets from the NDSU Extension Service which annually published crop budgets as a tool to assist farmers with planning their farming operations for specific regions of North Dakota (Swenson and Haugen 2021). These farm budgets provided selling prices per bushel and input costs per acre typical of the region in North Dakota for which they were estimated. These budgets included direct cost estimates (per acre) for seed, herbicides, fungicides, insecticides, fertilizer, crop insurance, fuel and lubrication, repairs, drying, miscellaneous, and operating loan interests. Indirect cost estimates from NDSU farm budgets included miscellaneous overhead, machinery depreciation, machinery investment, and land charge (e.g., rent or property tax). Indirect costs are often ignored by farmers when planning for individual years because they likely would not influence farmers' decision whether to cultivate a landform category in that year. However, indirect costs should be considered when a more long-term, whole-farm assessment of profitability is examined. I weighted indirect costs from the NDSU farm budgets by number of fields in each year and region. I added a second vertical (i.e., y-axis) to results figures to incorporate indirect costs (i.e., total costs) into profit. This was done through a simple subtraction of a weighted average indirect cost for all years of data from the profit estimations.

Revenue, Input, and Profit Calculations

I calculated revenue for each sampling grid point as the product of the yield and market selling price from the corresponding (i.e., appropriate crop type and year) NDSU farm budget estimates. Seed costs were calculated for each sampling grid point as the product of the number of seeds applied and the corresponding seed costs from NDSU farm budgets. I calculated all other direct costs from NDSU farm budgets for each grid point that had a seed rate associated to it (i.e., only applied to areas with planted seeds). Finally, I calculated profit as the difference between the revenue and direct costs for each grid point. Profits were averaged for each landform category within a field-year, but only for the area that was known to be planted (i.e., some field-years may have only planted a portion but not the whole landform) and may not represent the effect of the landform in its entirety on profit or yield. All monetary amounts reported are in US dollars.

Analytical Framework and Model Selection

I analyzed crop types (i.e., corn, soybean) separately to conduct variable selection methods more easily for each crop type. All models also tested the effects of landform on the dependent variable while controlling for other sources of variation that could be contributed to year and farmer identity. I also tested an interaction of year and landform for all models because variability in weather patterns from year to year may have affected farming management decisions and outcomes related to landform features.

Analysis

Area and Proportion Planted

I examined the average amount of area planted (hectares) in landforms as the response variable using a generalized linear model (GLM) from the "MASS" package (Venables and

Ripley 2002) in program R with a negative binomial distribution and a log link. The planted area data were analyzed with the average raster cell count (i.e., each cell was $4m^2$) for each landform in each field-year as the response variable and the resulting estimates were converted to area (i.e., acres/hectares). I examined the proportion of each landform planted response variable using a GLM from the "stats" package in program R with a binomial distribution and a logit link. For each response variable model, I report estimated marginal means averaged over year and farmer and 85% confidence limits from the top selected model. I evaluated differences between landforms based on confidence limits from one landform level overlapping the point estimate of another landform level.

Yield and Profit

I examined yield and profit of landform features using generalized linear models ("stats" package in R Statistical Computing Environment; R Core Team 2020) with normal distributions. I modeled the yield response variable at the grid scale as bushels per acre (bu/acre) and estimates were converted to megagrams per hectare (Mg/ha). I modeled the profit response variable at the grid scale and the estimates were converted to US dollars (USD) per hectare and acre. For each response variable model, I report estimated marginal means averaged over year and farmer and 85% confidence limits from the top selected model (Arnold 2010). I evaluated differences between landforms based on confidence limits from one landform level overlapping the point estimate of another landform level. Yield and profit estimates represent only proportions of each landform that were planted and do not represent the effect of the landform in its entirety because farmers presumably did not plant portions of landforms that were too wet. Direct-costs-only profit is reported in text and total costs are graphically displayed using offsets of $320.03 per ha and $129.51 per acre to account for corn total costs and $318.79 per ha and $129.01 per acre for soybean total costs.

Variable Selection

I evaluated predictor variables from the *a priori* full model by comparing one-variable-removed reduced models to the full model (Arnold 2010). I used the Akaike's Information Criterion adjusted for small sample size (AICc) (Burnham and Anderson 2002) to evaluate the reduced models. The removed predictor variable was considered informative if the AICc of the reduced model was increased >2 points compared to the full model. I first evaluated the year and landform interaction predictor variable, and it was removed if it was not considered informative. Next, year and farmer identity predictor variables were each removed to assess if the variable was informative. All informative predictor variables were included in the final reduced models. The final reduced models were compared to their corresponding *a priori* null models to evaluate their usefulness (Burnham and Anderson 2002).

Results

Profit analyses included 192 field-years planted to corn and 225 field-years planted to soybeans (Table 3.1). The yield analyses included 235 field-years planted to corn and 286 field-years planted to soybeans (Table 3.1) and covered >4,046 hectares. Crop field size ranged from 4.5–233.9 ha (11–578 acres) with a median size of 64.5 ha (159 acres). Median yields were 9.8 and 2.5 Mg per ha (157 and 40 bushels per acre) for corn and soybeans, respectively. Temporary and seasonal wetlands had median sizes of 0.91 ha (2.3 acres) and 3.50 ha (8.7 acres), respectively.

Table 3.1. Precision agriculture yield and profitability data acquired from four producers in southeastern North Dakota, 2003-2021. Not all fields had data available for every year.

Corn Field-Years					
Farmer	**Years**	**Year Range**	**Fields**	**Profitability**	**Yield**
A	9	2011–2020	25	68	97
B	4	2010–2018	1	NA	4
C	5	2017–2021	20	39	41
D	16	2003–2018	15	85	93
Total	18		61	192	235

Soybean Field-Years					
Farmer	**Years**	**Year Range**	**Fields**	**Profitability**	**Yield**
A	9	2011–2020	25	95	103
B	7	2003–2017	1	NA	7
C	5	2017–2021	24	41	77
D	16	2003–2018	15	89	99
Total	18		65	225	286

Model Selection

The predictor variable interaction of year and landform was not an informative parameter in any of the evaluated models for any of the dependent variables. Each final reduced model included predictor variables of landform, year, and farmer identity. Each final model had a lower AICc than it’s corresponding *a priori* full and null model (Tables 3.2 and 3.3).

Table 3.2. Models including predictor variables for each modeled response variable for corn. These data include the response variable, model group, AIC$_C$ scores (AIC$_C$), change in AIC$_C$ score from the top ranked model (ΔAIC$_C$), the number of predictor variables in each model (K), and model AIC$_C$ weight. Landform was included in all models. A landform interaction with year was included in the full model.

		Corn			
Response	**Model**	**AIC$_C$**	**ΔAIC$_C$**	**K**	**AIC$_C$ weight**
Profit	Year + Farmer	-1619.0	0.0	29	1.0
	Full	-1597.5	21.5	165	0.0
	Year	-1592.2	26.8	27	0.0
	Farmer	-1112.6	506.4	12	0.0
	Null	-1032.3	586.7	20	0.0
Yield	Year + Farmer	19327.6	0.0	31	1.0
	Year	19392.8	65.2	28	0.0
	Full	19432.8	105.3	175	0.0
	Farmer	20050.6	723.0	13	0.0
	Null	20202.3	874.7	2	0.0
Planted Acres	Year + Farmer	30633.4	0.0	29	1.0
	Full	30668.1	34.7	165	0.0
	Year	30690.4	57.0	27	0.0
	Farmer	30738.8	105.4	12	0.0
	Null	32354.4	1721.0	2	0.0
Percent Planted	Year + Farmer	1032.9	0.0	24	1.0
	Year	1046.1	13.2	22	0.0
	Full	1171.6	138.8	92	0.0
	Farmer	1178.1	145.3	7	0.0
	Null	1252.1	219.3	1	0.0

Table 3.3. Models including predictor variables for each modeled response variable for soybeans. These data include the response variable, model group, AICc scores (AICc), change in AICc score from the top ranked model (ΔAICc), the number of predictor variables in each model (K), and model AICc weight. Landform was included in all models. A landform interaction with year was included in the full model.

Soybeans					
Response	**Model**	**AIC_C**	**ΔAIC_C**	**K**	**AIC_C weight**
Profit	Year + Farmer	-3348.5	0.0	30	0.9
	Year	-3343.2	5.3	28	0.1
	Full	-3323.7	24.8	174	0.0
	Owner	-2481.5	867.0	12	0.0
	Null	-2452.5	896.0	2	0.0
Yield	Year + Farmer	17375.9	0.0	31	1.0
	Full	17574.7	198.9	175	0.0
	Year	17594.9	219.1	28	0.0
	Owner	18205.8	829.9	13	0.0
	Null	18299.1	923.3	2	0.0
Planted Acres	Year + Farmer	35624.0	0.0	30	1.0
	Year	35637.4	13.5	28	0.0
	Full	35686.6	62.6	174	0.0
	Owner	35754.7	130.7	12	0.0
	Null	37560.8	1936.9	2	0.0
Percent Planted	Year + Farmer	1175.7	0.0	25	1.0
	Year	1227.9	52.2	23	0.0
	Full	1305.6	129.9	97	0.0
	Owner	1318.9	143.2	7	0.0
	Null	1465.6	289.8	1	0.0

Area Planted

Planted area of each landform was similar between corn and soybean fields for most landforms but soybean planted area had a slightly higher point estimate for most landforms (Figure 3.1, Appendix B (Tables B.1 and B.2)). A slightly higher area per landform was planted with soybeans in sink3 and temporary wetlands compared to corn planted in those landforms. A similar number of hectares was planted for seasonal wetlands between the two crop types and for seasonal wetlands planted with corn and temporary wetlands with either crop. Sink3 had a lower number of hectares planted than temporary and seasonal wetlands and had a slightly higher area of soybean hectares compared to corn hectares planted. Sink2 had the lowest number of hectares planted whereas sink1 had the highest. The number of hectares was similar between corn and soybeans for sink1 and also similar between crop types for sink2 (Figure 3.1, Appendix B (Tables B.1 and B.2)).

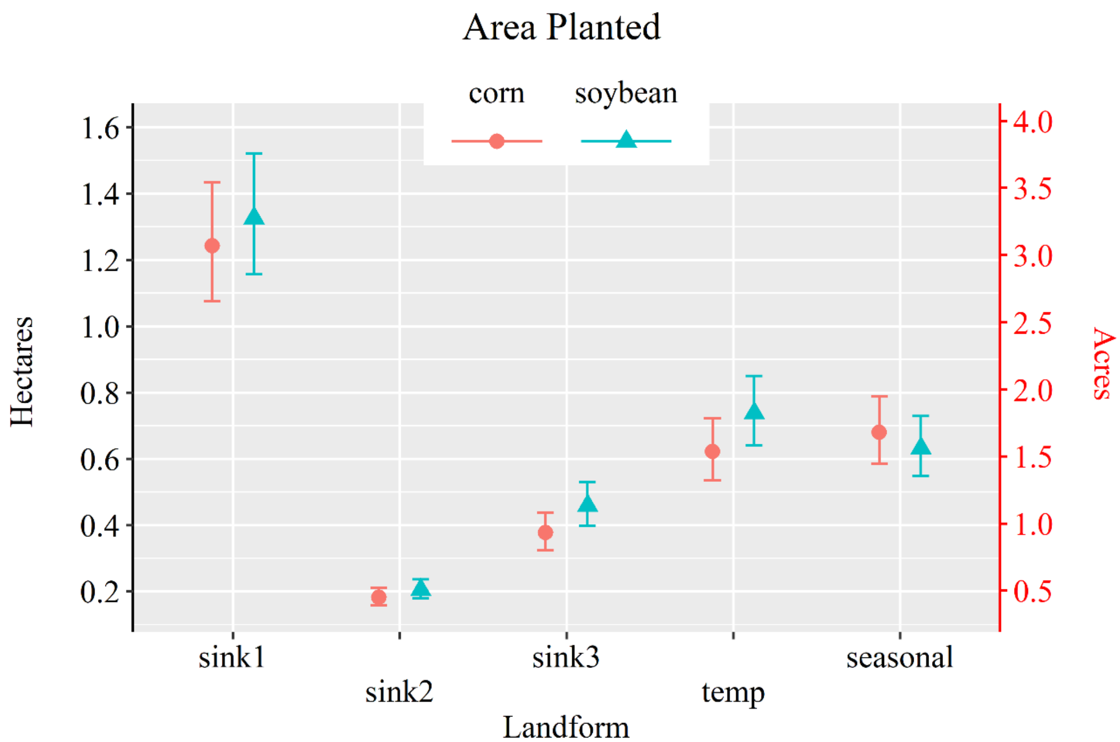

Figure 3.1. Average area of corn (red circles) and soybean (blue triangles) planted for each landform with 85% confidence limits. The left y-axis depicts area in hectares and the right y-axis depicts area in acres. Soybean upland area planted was estimated at 33.3 hectares, while planted upland area for corn was 30.2 hectares. Estimates were averaged over year and farmer.

Proportion of Landform Planted

Over half of the area of temporary wetlands were planted; specifically, proportions of temporary wetlands planted averaged 0.52 (CI = 0.45–0.6) and 0.55 (CI = 0.49–0.62) planted for corn and soybeans, respectively (Figure 3.2, Appendix B (Tables B.3 and B.4)). For seasonal wetlands, the proportions planted averaged 0.29 (CI = 0.23–0.35) and 0.32 (CI = 0.26–0.38) for corn and soybeans, respectively. The highest estimates for proportion planted were for sink1 areas for corn and soybeans. Sink2 and temporary wetland were similar in proportion of the landform planted. The proportion of area planted for sink3 was lower than that of sink2 and temporary wetlands while seasonal wetlands had the lowest proportion of the landform planted. Proportion of each landform planted was similar between corn and soybean fields with soybean planted areas having a slightly higher estimate for most landforms.

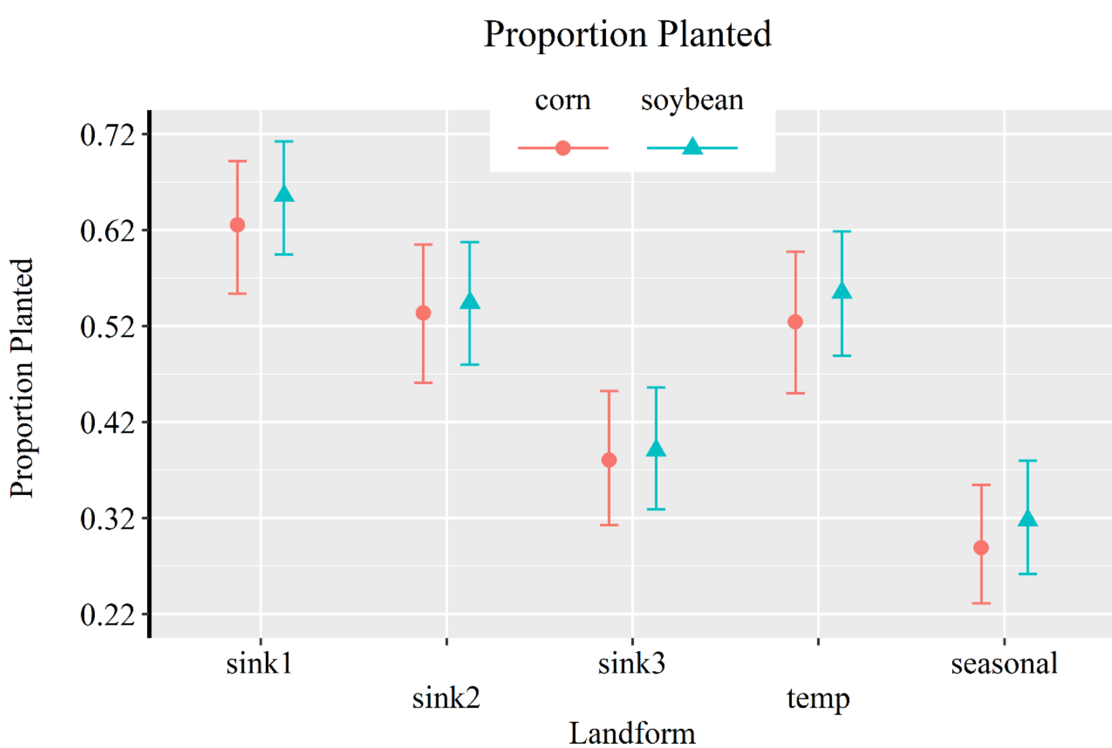

Figure 3.2. Proportion of each landform planted in corn (red circles) and soybean (blue triangles) fields with 85% confidence limits. The left y-axis depicts area in hectares and the right y-axis depicts area in acres. Estimates were averaged over year and farmer.

Yield

Corn yield estimates were highest for uplands and lowest in cultivated portions of seasonal wetlands (Figure 3.3, Appendix B (Table B.5)). Cultivated portions of dist10, sink2, sink3, and temporary wetlands had similar corn yield estimates to each other and were less than upland estimates. Dist30, dist20, and sink1 had similar corn yield estimates to each other and were lower than upland corn yield estimates.

Soybean yield estimates for cultivated portions of sink1, sink2, sink3, and temporary wetlands were similar to soybean yield estimates for uplands (Figure 3.4, Appendix B (Table B.6)). Dist30, dist20, dist10, and seasonal wetlands had similar soybean yield estimates and were lower than upland soybean yield estimates.

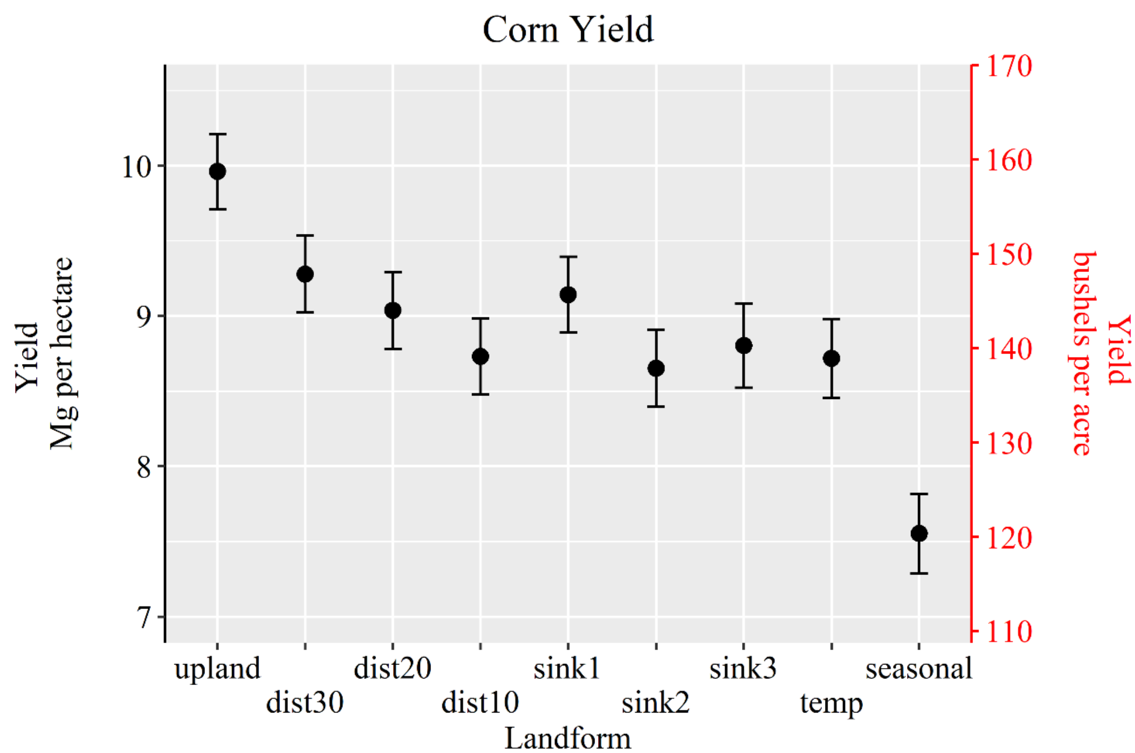

Figure 3.3. Corn yield estimates with 85% confidence limits for each landform from the portions of the landform planted. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. Estimates were averaged over year and farmer.

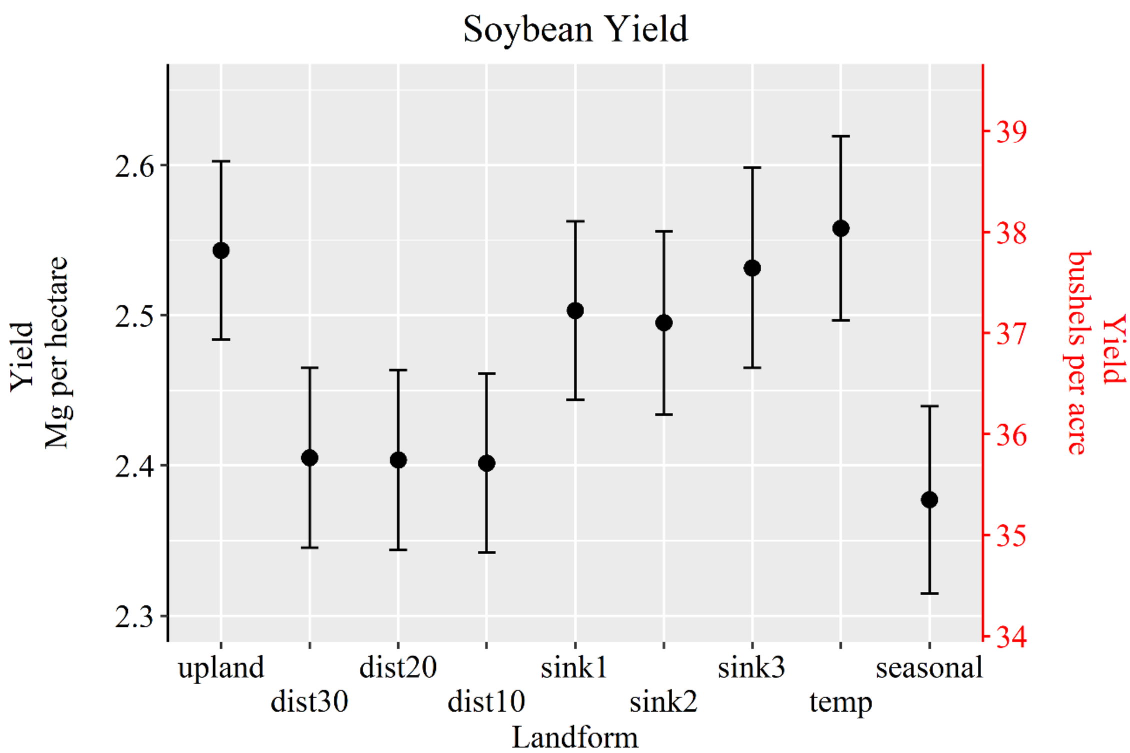

Figure 3.4. Soybean yield estimates with 85% confidence limits for each landform. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. Estimates were averaged over year and farmer.

Profit

Corn profit was highest for uplands and lowest for seasonal wetlands (Figure 3.5, Appendix B (Table B.7)). All other corn profit estimates were lower than upland estimates. Corn profits were similar for cultivated portions of dist30, dist20, and sink1. Corn profit estimates for dist10 were similar to dist20 and sink1 estimates. Corn profit estimates were similar to each other for cultivated portions of sink2, sink3, and temporary wetlands.

Soybean profit was highest for uplands and was lower than uplands for all profit estimates for cultivated portions of landforms (Figure 3.5, Appendix B (Table B.8)). Dist30, dist20, dist10, sink1, and temporary wetlands had similar profit estimates for the cultivated portions of the landforms. Soybean profit estimates for the cultivated portions of sink2, sink3, and seasonal wetlands were similar to each other and had the lowest soybean profit estimates.

Each landform estimate for corn profit was higher than its respective landform profit estimate for soybean (i.e., corn upland profit was greater than soybean upland profit). Corn profits from cultivated portions of sink2, sink3, and temporary wetlands were similar to soybean profit in upland areas. Corn profit from cultivated portions of seasonal wetlands were similar to dist30, dist20, dist10, sink2, sink3, and temporary wetlands.

Cultivated portions of seasonal wetlands had the highest frequencies of financial losses while sink1 had the lowest for direct-cost-only total cost corn profit (Tables 3.4, 3.5, 3.6, 3.7). Cultivated portions of sink1 and temporary wetlands for soybeans had the lowest frequency of financial loss while sink2 had the highest frequencies of financial losses (Tables 3.4, 3.5, 3.6, 3.7).

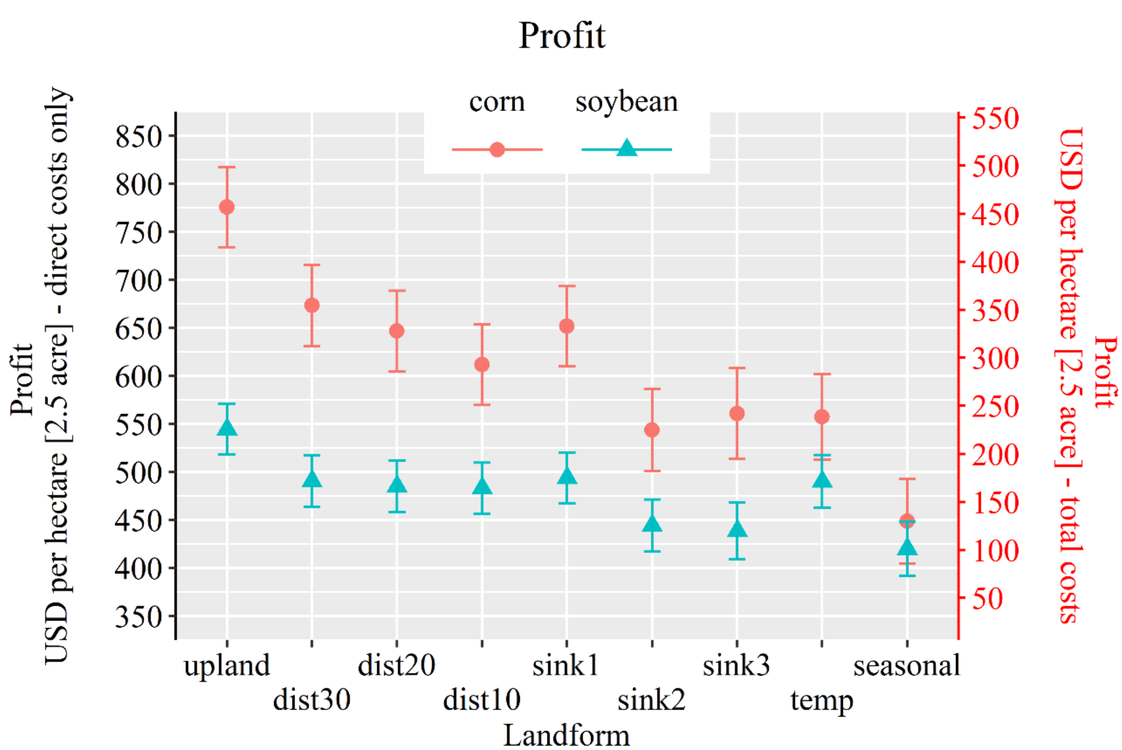

Figure 3.5. Corn (red circles) and soybean (blue triangles) profit estimates with 85% confidence limits for each landform. The left y-axis depicts profit in USD per acre (0.4 ha) when profit is calculated with only direct costs, excluding indirect costs. The right y-axis depicts profit in USD per acre (0.4 ha) when profit is adjusted for total cost (i.e., includes direct and indirect costs). Estimates were averaged over year and farmer.

Table 3.4. Total field-years for each farmer and landform, number of field-years where direct-cost-only profit for the farmer-landform combination was a financial loss (i.e., profit was less than 0 USD), the percentage of field-year losses, and the overall percentage of field-year losses for each farmer.

		Corn			**Soybeans**		
Farmer	**Landform**	**Field-years**	**Losses**	**%**	**Field-years**	**Losses**	**%**
A	sink1	68	1	1	95	3	3
A	sink2	62	7	11	88	4	5
A	sink3	51	2	4	74	8	11
A	temp	58	3	5	84	4	5
A	seasonal	56	7	13	78	4	5
C	sink1	39	1	3	41	0	0
C	sink2	39	7	18	41	7	17
C	sink3	38	11	29	39	10	26
C	temp	37	6	16	40	0	0
C	seasonal	34	4	12	39	1	3
D	sink1	85	11	13	89	2	2
D	sink2	85	16	19	89	8	9
D	sink3	85	13	15	89	12	13
D	temp	80	19	24	83	4	5
D	seasonal	85	24	28	89	7	8

Table 3.5. Total field-years for each landform, number of field-years where direct-cost-only profit for the landform was a financial loss (i.e., profit was less than 0 USD), and the percentage of field-year losses.

	Corn			**Soybeans**		
Landform	**Field-years**	**Losses**	**%**	**Field-years**	**Losses**	**%**
sink1	192	13	7	225	5	2
sink2	186	30	16	218	19	9
sink3	174	26	15	202	30	15
temp	175	28	16	207	8	4
seasonal	175	35	20	206	12	6

Table 3.6. Total field-years for each farmer and landform, number of field-years where total-cost profit for the farmer-landform combination was a financial loss (i.e., profit was less than 0 USD), the percentage of field-year losses, and the overall percentage of field-year losses for each farmer.

		Corn			Soybeans		
Farmer	**Landform**	**Field-years**	**Losses**	**%**	**Field-years**	**Losses**	**%**
A	sink1	68	13	19	95	21	22
A	sink2	62	19	31	88	29	33
A	sink3	51	13	25	74	18	24
A	temp	58	13	22	84	17	20
A	seasonal	56	23	41	78	23	29
C	sink1	39	10	26	41	10	24
C	sink2	39	22	56	41	18	44
C	sink3	38	18	47	39	18	46
C	temp	37	15	41	40	9	23
C	seasonal	34	10	29	39	10	26
D	sink1	85	25	29	89	14	16
D	sink2	85	32	38	89	20	22
D	sink3	85	28	33	89	22	25
D	temp	80	34	43	83	16	19
D	seasonal	85	44	52	89	26	29

Table 3.7. Total field-years for each landform, number of field-years where total-cost profit for the landform was a financial loss (i.e., profit was less than 0 USD), and the percentage of field-year losses.

	Corn			Soybeans		
Landform	**Field-years**	**Losses**	**%**	**Field-years**	**Losses**	**%**
sink1	192	48	25	225	45	20
sink2	186	73	39	218	67	31
sink3	174	59	34	202	58	29
temp	175	62	35	207	42	20
seasonal	175	77	44	206	59	29

Discussion

Farmers regularly cultivate within temporary and seasonal wetlands. Because of the water ponding characteristics of wetlands, cultivating within wetlands can come with increased risk of financial loss. Although farmers may be aware of the risk, often these practices continue which may be driven by multiple factors and one of those factors could be a lack of examining multi-year and multi-field metrics related to cultivating wetlands. My results suggests that farmers are cultivating relatively small areas of each wetland-related landforms (e.g., sink1, sink2, sink3, temporary, seasonal wetlands) which was a little over half the area of temporary wetlands and nearly one third the area of seasonal wetlands. However, the yield and profit within these areas are less than the rest of the field for most landforms and warrants a closer examination of yield and profit from wetland-related landforms.

Lower profit results in this study may be informative to farmers and conservation efforts because these data are often examined by farmers at the field or whole operation rather than subfield level (Cortus et al. 2011; Fey et al. 2016; Clare et al. 2021). These data need further examination with weather and other land features but are similar to other studies. Cultivating wetlands resulted in economic losses in four of the nine years included in the Fey et al. (2016) study. In addition, their analysis also indicated the return on investment was lower in the wetlands than uplands in eight of the nine years encompassed by their study. Clare et al. (2021) echoed the perception that farmers in their study of Canadian canola fields often failed to examine long-term sub-field profitability across their fields and years. While farmers understood that there was less profit when obtained when cultivating wetland areas than the rest of the field, they underestimated the magnitude of that difference. The underestimation of lowered profits or financial losses by farmers may also be occurring in this study given the frequency of financial losses. The one-year study from Clare et al. (2021) found a 56% financial loss across all fields for drained and consolidated wetland basins compared with only 30% loss in the undrained basins. One producer reportedly had a 90% loss on all drained and consolidated basins. My study shows frequency of losses for soybeans in temporary wetlands as 20% and in seasonal wetlands as 29% and corn in temporary wetlands as 35% and in seasonal wetlands as 44% from 19 years of data. Although, the two studies from Iowa and Alberta were in the PPR, the Iowa study was in an area with substantially more drainage infrastructure and increased precipitation levels. Also, the Canada study was for only one year and one crop type, which does not inform long-term profitability under a rotational cropping system. However, the losses on drained and consolidated basins suggests that those areas likely will not produce consistent yields and profits similar to uplands, despite the areas being drained. The results of Fey et al. (2016) and Clare et al. (2021) identifies a farming practice (i.e., cultivating wetlands) that could be adjusted by looking at them in a more long-term and total-cost profit modeling scenario that could benefit both farmers and conservation.

The number of field-years where sinks and wetlands were planted and the frequency of financial loss in both the direct-cost-only and total-cost profit calculations suggest that these areas are commonly farmed despite increased risk of financial loss compared to uplands. Wetland and sink landforms are often prepped (e.g., disked) for planting in the autumn or early spring which incurs both direct and indirect costs. However, spring water conditions may not allow for planting and would therefore not incur further direct costs but typical input costs considerations for profit calculations may disregard the initial planting preparation costs. Lowered yield and profit in wetlands are not new concepts for farmers but often little formal subfield level examination for wetland areas occurs (Clare et al. 2021). Proportion of landform planted may help to inform a realistic approximation of area on which direct costs could be incurred. Also, knowing the extent of the area of landforms that get planted may provide more realistic estimates of waterbird habitat in cropland landscapes which in turn may influence conservation efforts. Low to mid ranges of vegetation cover was shown to benefit dabbling ducks and some shorebird species (see Chapter 2).

Continuation of normal farming management practices (e.g., cultivating wetlands when possible) may relate in part to the size of wetland and sink related areas. These areas are often small (< 2 acres) and have been noted as an inconvenience for farmers to drive around (Cortus et al. 2009). However, soybeans had slightly higher number of hectares planted for most landforms and may be the result of a farming practice where farmers seed or plant low spots at a later date compared to the rest of the field so the low areas have time to dry which can then be accessed by machinery with less chance of getting stuck in saturated soils (Kandel and Endres 2019; Ransom 2019). Yet, the later plantings do not always occur and the unplanted areas of these landforms in this study were assumed to have resulted from issues related to ponded water that prevented farm machinery from easily traversing the landform. This is evident from the proportion planted analyses where approximately 53% and 31% of temporary and seasonal wetland area was planted, respectively. The central and deeper parts of these wetlands were assumed to be the unplanted areas and were therefore likely idled (i.e., left unmanipulated by farm machinery) in some years. Therefore, different modeling scenarios should be examined to consider the whole area of wetland landforms in profit calculations.

The proportion of wetland landform area not planted, and combined with the small size of these areas, lower yield, and lower profit estimates compared to uplands, should be seen as a mutual motive for conservation planners to provide farmers an option to gain income while also helping optimize the natural ecosystems services the agricultural wetlands provide. For farmers this could be an opportunity to increase profit or have more consistent profit in areas that are sometimes idled and could reduce the time and effort put into managing these areas. For conservation, this could be an opportunity to keep temporary and seasonal wetlands from being drained and increase the amount of wildlife habitat in an area vital to shorebird and waterfowl populations.

The yield and profit analyses in this study provided evidence that landform features described in this study affect those metrics. It is also known that yield, and consequently, profit are affected by other environmental factors such as soil variability, precipitation, and evapotranspiration (Muth 2014; Fey et al. 2016). Therefore, there is need for further examination of other temporally and spatially explicit environmental data, such as temperature and precipitation data, that may be necessary to understanding these processes (see Chapter 4). Those analyses would provide better insights for conservation planning.

Even without subfield level data, some farmers may know the areas in their fields where the yield is lower or more variable and where they have ponded water issues, but there may be multiple reasons why they continue cultivating these areas, some of which are likely driven by financial influences, social influences (Chenard and Parkins 2010), and government policy (Lark et al. 2015; Brandes et al. 2016). Keeping land qualified for prevented plant insurance was noted as an influence on farmers on whether to attempt to cultivate a low spot or wetland (see Chapter 5) and suggests these results may also help to inform wetland related policy decisions to improve policies' influence on conservation while still providing benefits to farmers. The data in this study can provide relatable numbers for acres planted per landform and how much of the landforms are regularly planted which would be beneficial for planning region-wide conservation efforts in North Dakota's Drift Prairie. Yield and profit estimates from this study can inform farmers as to what to expect for those subfield level metrics on their operation in the

Drift Prairie but farmers and planners may be better served to assess yield and profit under varying weather conditions (see Chapter 4).

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CHAPTER 4. YIELD AND PROFIT IN CULTIVATED DEPRESSIONAL WETLANDS AFFECTED BY ENVIRONMENTAL CONDITIONS IN SOUTHEASTERN NORTH DAKOTA

Abstract

Wetlands of the Prairie Pothole Region in North America provide many ecosystem services to humans. While many of the natural ecosystem services provided by wetlands have been studied, less is known about agricultural services provided by wetlands. I analyzed 19 years and over 4,000 hectares of precision agricultural data from corn and soybean fields in the Drift Prairie in North Dakota to estimate yield and profit in landform features and in relation to variations in weather, field topography, and a soil productivity index. For all types of wetlands and depressional areas, yield and profit from both corn and soybeans declined with increasing wetter weather. Under average weather conditions during early summer, average direct-cost-only profit was 22% less in cultivated portions of temporary wetlands and 34% less in cultivated portions of seasonal wetlands than in upland areas. However, when the entire wetland area was considered in profit calculations, average crop profit was 48% less in temporary wetlands and 64% less in seasonal wetlands than that of upland areas. Yield responded similarly to the variables examined and included as informative in each model. Although, wetland and depressional areas were profitable in certain scenarios, the lowered profits and yields compared to uplands, may be an opportunity for conservation efforts to incentivize alternative management of these wetlands and help farmers increase their profitability. This study is the first known to provide profit and yield estimates for wetland-related landforms in the Drift Prairie of North Dakota and highlights an opportunity for conservation efforts to improve management of

agricultural wetlands which could provide better financial outcomes to farmers while also enhancing or preserving wildlife habitat.

Introduction

Wetlands of the Prairie Pothole Region (PPR) provide important natural ecosystem services that are realized throughout central North America (e.g., floodwater attenuation, maintenance of water quality, carbon sequestration, wildlife and livestock forage, and wildlife habitat (Kirby et al. 2002; Gleason et al. 2008; Brinson and Eckles 2011). Wetlands in this region reduce flooding and contribute to water quality on major waterways in North America, such as the Red, Missouri, and Mississippi Rivers (Hey 2002; Zedler 2003; Gleason et al. 2011; Anteau et al. 2016). In the spring and fall, millions of migrating and breeding waterfowl and shorebirds use PPR wetlands for foraging and brood rearing (Kroodsma 1979; Batt et al. 1989; Cox et al. 1998; Euliss et al. 1999; Krapu et al. 2006; Anteau and Afton 2009). Due to the abundance of wetlands in this region, the PPR is breeding habitat for >50% of the North American duck population (Batt et al. 1989). Wetlands with more ephemeral hydroperiods are often cultivated when situated within agricultural fields. While there has been considerable research on quantifying natural ecosystem services provided by wetlands (e.g., Daily et al. 2000; Woodward and Wui 2001; Jenkins et al. 2010; Gascoigne et al. 2011), very little attention has been paid to evaluating the services wetlands provide through agriculture and understanding the tradeoffs of these natural and agricultural ecosystem services provided.

Wetlands of the PPR are classified by hydroperiod (Stewart and Kantrud 1971), but their function is related to a continuum of atmospheric and groundwater water input dynamics (Euliss et al. 2004; Hayashi et al. 2016). Water level dynamics in PPR wetlands are primarily dictated by snow melt and spring precipitation, which result in temporary wetlands retaining water for short periods (14–28 days) and seasonal wetlands typically holding water for 30–90 days (Dahl 2014). Prior to European settlement, the functions and vegetation characteristics of PPR wetlands were influenced by natural disturbances, such as fire, large grazers, and water dynamics, which left a mosaic of vegetation patterns across the region and within wetlands.

PPR wetlands and surrounding uplands have experienced considerable change in land use during recent decades. Prior to the major land-use changes of the of the last 100-150 years, the landscape of the PPR was an expansive grassland with scattered depressional wetlands. Agricultural development and cultivation have fragmented the pre-European landscape and modified water dynamics, disturbances, and vegetation characteristics of wetlands. Recent increases in conversions of wetlands to cropland have raised concerns regarding the ability of the PPR to continue to provide adequate habitat, such as stopover and refueling habitat for migrating waterbirds (Skagen 1997; Anteau and Afton 2004; Eldridge et al. 2009; Anteau and Afton 2011).

Much of the PPR is privately owned and has been converted to cropland, but some areas have recently experienced a greater rate of conversion. In North Dakota, there has been an increase in the amount of land in agricultural production over the past 50 years because of commodity prices, land values, and government programs and policies (Lark et al. 2015; Brandes et al. 2016). North Dakota was identified as a ‘hotspot’ of new cultivation with most of the cropland expansion located east of the Missouri River within the Prairie Pothole Region (PPR) (Lark et al. 2015). The expansion of cropland has resulted in the conversion of many areas of agriculturally less productive lands (e.g., wetlands) and grasslands into agricultural production. Parts of the PPR have lost 50–90% of original wetlands to drainage (Dahl 1990) and wetlands are continuing to be drained (Werner et al. 2016). For example, 55,000 hectares of wetlands were converted to cropland from 2008–2012 in North Dakota, South Dakota, and Minnesota that had not been cultivated since at least 2001 (Lark et al. 2015). A threefold increase in corn and soybean prices occurred during 2002–2012 and likely contributed to the increase in wetland cultivation (Johnston 2013) and in continued wetland drainage (Werner et al. 2016).

More than 80% of remaining temporary and seasonal wetlands in North Dakota's Drift Prairie, a physiographic region within the PPR, are located within annual crop or alfalfa fields (Niemuth et al. 2006); hereafter I will refer to these wetlands as agricultural wetlands (AW). Frequently AW are cultivated, a process of manipulating them in preparation for planting a crop, planting a crop, or harvesting crop. Agricultural wetlands that have not been drained or filled are cultivated regularly, (e.g., temporary wetlands) or periodically (e.g., seasonal and semi-permanent wetlands) when conditions are dry enough to operate machinery within them. AW can often be disked in the late fall when wetlands are dry, but many times water dynamics in the spring may prevent or delay crop planting.

Much of the success growing, harvesting, and profiting from cultivating crops within an AW is determined by timing and magnitude of precipitation events. The unpredictability of winter and spring precipitation events results in greater economic uncertainty when cultivating AW than in the surrounding uplands because of the capability of wetlands to pond water. Economic losses may occur during any part of cultivating AWs, but financial losses greater when a crop has been planted and subsequently killed by ponded water following a precipitation event (DeBoer and Ritter 1970; Lizaso and Ritchie 1997; Sullivan et al. 2001; Zaidi et al. 2004). That loss is greater because the later crop failures would have a greater investment of direct costs (i.e., fertilizer, fungicide, herbicide, etc.); however, seed costs can be one of the most expensive direct input costs on a per area basis (Swenson and Haugen 2021). Two or more days of ponded water over a planted crop can result in a yield reduction or complete loss of the crop (i.e., drown-out with no crop yield) within the ponded water area (Wenkert et al. 1981; Rhine et al. 2010; Bailey-Serres et al. 2012).

Many farmers across the Drift Prairie continue to cultivate AW despite higher financial risk (Fey et al. 2016; Clare et al. 2021). Profit (i.e., revenue minus input costs) seeking has been shown to influence other farming management decisions (Arbuckle 2015; Plastina et al. 2020) and may be a reason farmers continue cultivating AW. There are multiple reasons why farmers continue this practice such as trying to reduce compaction of soils when driving around wetlands, the ease of driving through rather than around, the potential income from cultivating additional land (assuming a successful AW crop), or the potential to get insurance coverage on the planted area to protect against crop loss (Cortus et al. 2011). Regardless of the reason, it remains unclear whether cultivating AW is consistently profitable for farming operations across multiple years in the Drift Prairie.

The ability to assess both yield and profitability at fine resolutions (~ 20-30 m^2) within a field has been facilitated by precision agriculture (PA) technologies. PA technologies have allowed farmers to track inputs (e.g., seeding rates, fertilizer rates, etc.) and crop yields at a fine resolution using global positioning systems integrated with their machinery (Muth 2014; Brandes et al. 2016; Fey et al. 2016; Schimmelpfennig 2016). The goal of PA is to increase profitability by allowing producers to optimize management practices at the sub-field level (Lerch et al. 2005; Schimmelpfennig 2016; Long et al. 2016; Lindblom et al. 2017; Paustian and Theuvsen 2017). While this technology has impressive capabilities, it requires time and effort to use effectively, as well as new skill sets of producers such as data stewardship, spatial data processing, and sensor calibrations. As a result, farmers often only view yield monitors and yield maps to get a general sense of their yield for the current harvest and may not aggregate years of their input and harvest data to thoroughly examine their sub-field operations (Lachia et al. 2021), which could help to assess the profitability of cultivating less productive lands such as AW (Clare et al. 2021).

If farmers are unaware of the long-term profitability or magnitude of loss from cultivating in and around AW, they are unlikely to explore different management options for those areas, which could increase overall farm profit. Therefore, I examined yields and profitability derived from long-term (19 years), aggregated PA data under varying precipitation and evapotranspiration to increase understanding of the role that AWs play in the profitability of farming operations in the Drift Prairie of North Dakota. This study may better inform a monetary incentive amount that would be more attractive to farmers to forgo typical operations within AW. Determining alternative management strategies or uses of AW includes many unknown variables such as determining farmers perspectives and expectations relating to cultivating AW. However, a first step is to determine farmers' financial stake in AW which involves examining the profitability of cultivating AW.

Methods

Study Area

The PA data in this study came from corn-soybean rotational cropping systems, which is common in the Drift Prairie of southeastern North Dakota. Prior to European settlement, the PPR was a vast grassland interspersed with depressional wetlands. In the Drift Prairie, the highest wetland densities can reach >57/km^2 (Dahl 2014), mainly composed of temporary and seasonal wetlands. Most wetlands are <0.5 ha in area but can reach sizes of >40 ha for permanent bodies of water (Kantrud et al. 1989; Batt 1996; Niemuth et al. 2010). However, the gently rolling landscape made the Drift Prairie conducive to cultivation and thus land use was predominantly agriculture. During 2017, 73% of land from counties fully residing within the Drift Prairie of North Dakota was designated as cropland (NASS 2017).

Annual precipitation in North Dakota typically ranged from 40.6 cm (16 inches) in the northwest to about 60 cm (24 inches) in the southeast. The wettest consecutive 5-year period since 1900 was from 2007–2011 (Frankson et al. 2022). July temperatures in North Dakota range from 18.3–22.2°C (65–72°F).

Field Data

I acquired precision agriculture data from four farmers. These data included planting and harvesting data for most crop fields and years. Field-year is designated as the unique combination of a crop field in each year because there were different crops and environmental conditions resulting in different extents of crop fields in each year and therefore, data were not available in all years for every field. Field data was missing for various reasons, some of which included crops other than corn or soybeans were planted in the field or the farmer did not provide the data. The PA data type available for a crop field had the potential to change from year to year. PA data were collected by different makes, models, and types (e.g., combine harvesters, planter) of machinery and software, but each point had location information associated with other data such as the name of the crop field (assigned by farmers), date, crop type, seeding rate, yield obtained, moisture content, product flow rates, or grain mass. I aligned common ancillary data into a common system and converted it to geospatial point format (e.g., point shapefile) for further manipulations and visualizations.

Harvest Data

Harvest data collected from combine harvesters (i.e., farm machinery which reaped, threshed, gathered, and winnowed grain crops) periodically contains errors in yield estimates for various reasons; most commonly they are attributed to partial swaths of grain into the header of the harvester, time lag of grain from collection to grain flow sensors, geo-positional errors, surging grain through the system, rapid velocity changes of the harvester, grain loss, and sensor accuracy (Blackmore and Marshall 1996). These errors pose challenges for mapping and accurate inference, so various procedures are typically used to flag, filter and smooth the data (Blackmore and Marshall 1996; Thylén et al. 2000; Sudduth and Drummond 2007). Existing methods had the potential to bias data, so I modified some of the standard methods used by the agriculture industry.

Yield Editor 2.0 (YE2) (Sudduth et al. 2012) software was used to clean the yield errors. Sudduth et al. (2012) explored the options available to flag/filter data points, provided best practices to use the YE2 software, and provided explanations of the calculations used to set filter limits. I used program R (R Core Team 2020) to convert spatial data into YE2-readable text files, write YE2 settings files and batch files, and run the batch files which programmatically started and sent data into YE2 for each field-year yield file. I used settings files to specify which errors to flag and to select the "automated yield cleaning expert" (AYCE) mode which automatically chose flag limits or criteria for the data based on internal evaluations. Some of the limits flagged were minimum and maximum speed, minimum and maximum yield, minimum and maximum velocity, optimal grain flow corrections, optimal moisture corrections, local standard deviation errors, and others. I exported the YE2-processed field-year yield data to comma separated value (csv) files which included a code column that corresponded to the reason or reasons why each line of the data was flagged or not flagged as an error. Often YE2 users will remove data points flagged for being below a certain yield level assuming they are in error, however, these may be accurate data points and without other reasons (i.e., being flagged by additional AYCE codes), these data were considered accurate and used in further analysis. Removing data points solely for low yields may have biased these data and inhibited the ability to examine the low yield areas within a field and thus I removed all flagged data except data points which were flagged solely because of low yield.

I converted cleaned yield csv files back into geospatial point format using program R (R Core Team 2020). I then used ArcGIS v10.5.1 (ESRI 2019) to create a Model Builder (MB) workflow to automate interpolation of the yield data. The cleaned yield spatial point data were interpolated using ordinary kriging with a spherical semivariogram model, 2-m cell size for the output raster, and a variable search radius of 12 points or 25 m to create a raster for each field-year of available spatial data. Each cell value in the raster contained the interpolated yield estimate. I masked (i.e., bounded) interpolated yield raster for each field-year with a polygon resulting from aggregating and buffering (e.g., by approximately half of the machinery width) the original field-year's harvest spatial point data into a polygon with a 15-m aggregation distance. The mask polygon helped to exclude interpolation through areas where wider than normal gaps in the harvest data existed (e.g., driving around wetlands or other obstacles, or areas where the machinery did not record data).

Planting Data

Planting data was generally less prone to the number and type of errors than that of harvest data. These data were typically analysis-ready or were completely missing which occurred for 11% of field-years in this study. Some planting data had the correct spatial coverage but were lacking the rate of seeds applied to the field. Two of the three farmers that provided planting data used variable rated (VR) planting machinery for all years and the third farmer used VR planting in the last three of 15 years of data provided. Map-based (VR) technologies allow farmers to upload prescription maps into their machinery that contain farmer-defined subsections of fields where different programmed rates of products (i.e., seed, fertilizer, etc.) may be automatically adjusted and applied in the pre-defined area (Grisso et al. 2011). When VR planting was used by a farmer (known through personal communication) but the applied rate was not recorded for all the points in planting data, I either substituted a targeted yield rate (i.e., the intended rate of seeds planted) from a nearby crop field of the same crop type and year as a rate for the whole field; or if a prescription map was available for the field in that year, I used the targeted rates from that prescription map for the corresponding subsections of the field. The targeted rates were determined by farmers and were the desired amount of seeds to apply in a specific section of the field by the machinery. The data from the planting showed that machinery rarely planted the exact targeted rate of seeds (e.g., 28,000 seeds per acre) and usually applied slightly too few or too many (e.g., 27,876 seeds per acre) seeds but recorded the actual amount of seeds planted for each data point. The planting data were put through a similar (i.e., buffer adjusted for machinery width) ArcGIS MB interpolation workflow as the harvest data which generated raster files with the applied seed rate as the cell values.

Fertilizer and Chemical Application Data

Fertilizer and chemical (i.e., herbicide, fungicide, etc.) applications recorded data similar to planting data in that they had targeted rates and applied rates associated with each data point. However, the data for fertilizer and chemical applications from farmers were often unorganized and unreliable and therefore were not used in any analyses. I used North Dakota State University (NDSU) crop budget estimates in lieu of farmer supplied chemical and fertilizer data (described below).

General Adjustments to Precision Agriculture Data

There were instances where a field-year's planting and harvest data did not completely align because of missing or incomplete data. Visual examination of spatial data helped to determine if the missing data was purposely excluded (i.e., avoided wetland) or a recording error (i.e., missing rows across whole field). Often spatial data errors or machinery errors were displayed as straight line or row pattern (i.e., un-natural boundaries), whereas obstacle purposefully avoided had curved or angled spatial data segments that were congruous with the surrounding spatial data. I clipped planting spatial data to the layout of the harvest spatial data and discarded if, and where, the data were deemed to be recording errors, but were left intact if the differences were determined to be purposefully driven around as would be the case from avoiding a wetland with the machinery. One farmer frequently used multiple combine harvesters in the same field-year but did not collect all the data from each harvester, which left a random coverage of harvest information over the field. I processed these data in the following sequential steps: created a spatial polygon boundary by aggregating the harvest spatial point data with a 30m aggregation distance, then buffered the polygon to account for machinery width, and finally converted "holes" within the polygon that were less than 1.2 ha to part of the spatial polygon (i.e., Eliminate Polygon Part tool which made the holes become part of the polygon). I assumed areas larger than 1.2 ha to be recording errors. I used the resulting spatial polygon boundary for the boundary of the field for further harvest data processing.

Wetland Data

The National Wetlands Inventory (NWI) Database (USFWS 2018) was a readily available collection of digitized wetland polygons within the United States. This data layer contained many of the temporary and seasonal wetland areas that were present within the crop fields in this study. For temporary and seasonal wetlands within study crop fields, I converted the supplied vector data to raster data with a 2-m cell size and wetland type as the cell value. The NWI wetland boundaries were static across years of this study.

I also created a distance-from-wetland (DFW) raster layer, which classified raster cells by Euclidean distance to the nearest wetland into one of the following classes: dist10 (0–10 m), dist20 (10–20 m), and dist30 (20–30 m). Distance categories were multiples of the approximate width of machinery (10 m) which could have influenced farmers' navigation decisions. Also, cropland adjacent to wetlands within the PPR frequently have high soil salinity which may limit crop growth surrounding some wetlands (Seelig 2000; Franzen 2003).

Digital Elevation Models and Sinks

I acquired LiDAR-derived digital elevation model (DEM, https://lidar.swc.nd.gov/) raster data for every crop field in this study. The DEM had a vertical accuracy of ≤15.0 cm root-mean-square error (RMSE) and a horizontal accuracy of ≤1 m RMSE.

Many of the low spots within the crop fields of this study were delineated by the NWI wetlands data; however, I identified additional areas of relative lower elevation across fields, which were not in the NWI database and could potentially pond water and impact crop yields and profitability. To identify low spots, I used ArcGIS to mosaic (i.e., combine) overlapping DEM rasters together and clipped them with the boundary of each corresponding crop field. I processed the clipped rasters through a workflow to create spatial rasters that identified areas where low spots (i.e., sinks) occurred within the field. I defined sinks as a raster cell or cluster of cells that were lower in elevation than surrounding cells and had an undefined drainage direction. I created a "filled" raster through a process called filling where the cell elevations from the DEM were virtually raised until the raster cell would no longer pond water, i.e., the elevation of the cell was raised equal to the lowest elevation of an immediate neighbor (Planchon and Darboux 2002; McCauley and Anteau 2014). I then subtracted the original DEM from the filled raster which produced a sink raster (i.e., producing a raster with the depth of the sinks for each cell) (McCauley and Anteau 2014). The sink rasters were reclassified based on the depth assigned to each cell into the following classes: Sink1 (0–0.15 m), Sink2 (0.15–0.25 m), and Sink3 (>0.25 m). I chose the first interval to correspond with the vertical accuracy of the DEM. The result of this raster created many small (e.g., 1–4 cells) groups of raster cells displaying >0 m filled depth. I then used four repetitions of the "Majority Filter" tool in ArcGIS as a method to smooth and remove small clusters of >0 m depth cells. This process replaces cells in a raster based on the majority of its contiguous neighboring cells. Next, the raster was converted to polygons to be aggregated, spatially combined (i.e., union), and dissolved into a contiguous spatial polygon outlining the sink area. I then used these polygons to clip the "filled" raster (i.e., raster created right after the filling process). The resulting raster contained the raw (unclassified) depth values for each 1 m cell in the sink areas. I classified sink depth again into the Sink1, Sink2, and Sink3 category. Areas outside of the sink raster area was reclassified as 0 m depths. Sink raster layers were static across years.

Standardized Precipitation-Evapotranspiration Index (SPEI)

The SPEI is an index that estimated drought severity ranging from -5 (severe drought) to 5 (severe deluge) and is calculated using monthly precipitation and temperature averages (Vicente-Serrano et al. 2010; Abatzoglou et al. 2017). These data were raster layers with approximately 3700 m by 4700 m cells that contained an SPEI value. I acquired these data for each year with corresponding PA data. I chose a 4-month aggregation for both early- (March–June) and late-season (July–October) periods in which expected precipitation and temperature may have affected crop yields or the ability to plant or harvest a crop. I also used an 8-month aggregation for the months prior to the analyzed growing season to assess soil moisture from winter months. Ranges for early, late, and winter SPEI were -1.73–1.734, -1.87–2.59, and -1.87–2.59, respectively. Average values from the data in this study for early, late, and winter SPEI were -0.13, 0.72, and 0.62, respectively. The SPEI scale is standardized so "0" represents the long-term average for SPEI and can be compared across space and time. For reporting results, I used -1.70, 0, and 1.70 to represent low, average, and high SPEI values, respectively.

Landform Designation

I designated landform as a category to classify geospatial data points into specific land features that may affect crop yields and, in turn, profits for farmers. There was a hierarchal categorizing structure because some points may have been geospatially positioned in more than one landform class. For example, a point may have been geospatially located within a sink (e.g., Sink1) and a NWI wetland (e.g., temporary wetland). To address multiple classifications, I categorized each point into a class level from one of eight classes in the following order: NWI wetland class (temporary, seasonal), DFW class (dist10, dist20, dist30), and sink class (Sink1, Sink2, Sink3). The former classes of this category took precedence over the latter. I designated spatial points not identified in any of the previously defined classes as "upland" in the landform category.

Upland Productivity Index (UPI)

I derived UPI from the Natural Resources Conservation Service (NRCS) Soil Survey Geographic database (SSURGO) which included a National Commodity Crop Productivity Index (CPI) that evaluates the soils capacity to grow crops (Dobos et al. 2008; Web Soil Survey 2011). CPI ranges from 0 to 1, with 1 being the most productive for crops. Geospatial SSURGO soils polygon data were acquired for each field. I calculated UPI as the CPI weighted by the area of land that each soil polygon comprised in the upland landform (i.e., wetlands and sinks excluded) for each crop field. UPI was as a single, static across years number representing each field and it ranged from 0.549 to 0.914 for study fields.

Upland Slope Coefficient of Variation (USCV)

Elevation grade or slope can affect yield and other crop measurements (Kravchenko and Bullock 2002; Kravchenko et al. 2003; McKinion et al. 2010). I used the previously described DEM and the “Slope” tool in ArcGIS to calculate the maximum rate of change in elevation value from a cell to its immediate neighbors (i.e., slope) which produced a slope raster. I calculated the coefficient of variation (i.e., standard deviation divided by the mean) for slopes in the upland landform (USCV) for each field. I used the coefficient of variation of slope as a method to describe the slope of the upland area as a single predictor variable. Lower values of USCV described fields with a tighter range of slope variation and a higher mean slope estimate (i.e., more ruggedness). USCV was static across years for each field and ranged from 0.480 to 1.07 for the fields included in these analyses.

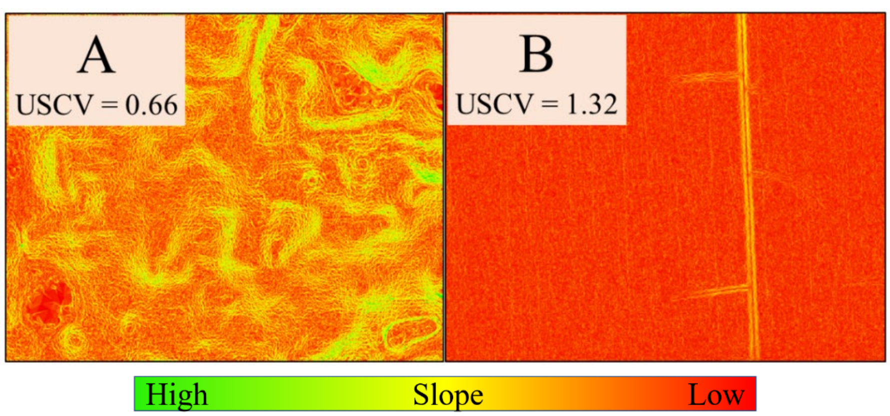

Figure 4.1. Slope raster for two crop fields in North Dakota with calculated USCV for each. The lower USCV slope raster (A) had a higher mean slope of upland area than its standard deviation and had a more rugged terrain. The higher USCV slope raster (B, field was not included in analysis) had a lower mean slope of upland area than its standard deviation and had a flatter terrain.

Sampling Grid and Raster Extraction

I created a 2 m by 2 m sampling grid using the "Create Fishnet" tool in ArcGIS, which created a point layer over the extent of each crop field. For every field-year, I used the "extract" function in the "raster" package (Hijmans 2020) in program R (R Core Team 2020) which pulled raster data at each point in the sampling grid from each raster layer available for that field-year into a single line of data (i.e., spreadsheet or tabular format). The grid point locations were maintained to sample the same locations across years. Each grid point had the potential of the following data associated to it: crop type, year, field name, farmer identification, yield, seeds applied, sink depth, NWI wetland type, and distance from NWI wetland. I designated empty cells in rasters with an "NA" to distinguish between "no data" values and "0" and therefore each grid point had an "NA" extracted from a raster layer if there was not data associated to that grid point location. However, yield was changed from "NA" to "0" for grid points which had non-empty planting rates (i.e., not missing or non-"NA" from the planting raster) and also had missing yield rates (i.e., "NA" from the yield raster). This was needed in circumstances where an area was planted but had no harvest data because the location was driven around because of a lack of harvestable crop or water obstacle. Further manipulation of "NA" cells is discussed below under the described farming scenarios.

Farm Budgets

Some farmers provided financial data, such as seed costs, but most did not provide adequate financial data to allow a complete assessment of profitability. To estimate input costs and selling prices, I used farm budgets from the NDSU Extension Service which annually published crop budgets as a tool to assist farmers with planning their farming operations for specific regions of North Dakota (Swenson and Haugen 2021). These farm budgets provided selling prices per bushel and input costs per acre typical of the region in North Dakota for which they were estimated. These budgets included direct cost estimates for seed, herbicides, fungicides, insecticides, fertilizer, crop insurance, fuel and lubrication, repairs, drying, miscellaneous, and operating loan interests. Indirect cost estimates from NDSU farm budgets included miscellaneous overhead, machinery depreciation, machinery investment, and land charge (e.g., rent or property tax). Indirect costs are often ignored by farmers when planning for individual years because they likely would not influence farmers' decision whether to cultivate a landform category in that year. However, indirect costs should be considered when a more long-term, whole-farm assessment of profitability is examined. I weighted indirect costs from the NDSU farm budgets by number of fields in each year and region. I added a second vertical (i.e., y-axis) to results figures to incorporate indirect costs (i.e., total costs) into profit. This was done through a simple subtraction of a weighted average indirect cost for all years of data from the profit estimations.

Revenue, Input, and Profit Calculations

I calculated revenue for each sampling grid point as the product of the yield and market selling price from the corresponding (i.e., appropriate crop type and year) NDSU farm budget estimates. Seed costs were calculated for each sampling grid point as the product of the number of seeds applied and the corresponding seed costs from NDSU farm budgets. I calculated all other direct costs from NDSU farm budgets for each grid point that had a seed rate associated to it (i.e., only applied to areas with planted seeds). Finally, profit was calculated as the difference between the revenue and direct costs for each grid point. Profits were averaged for each landform category within a field-year. All monetary amounts reported are in US dollars.

Known Farmed and All Farmable Land Scenarios

I wanted to assess different scenarios related to areas within a crop field that are cultivated in some but not all years. I assumed that the farmers' decisions to cultivate these areas were attributed to water levels. If water levels were at a level where a farmer could not get machinery into an area, then the area would appear in the planting raster as an "NA" value for those grid points in the associated year and therefore, did not have direct costs, (i.e., planting data) applied to those grid points. Direct costs may have been incurred the previous fall for land preparation, but I did not have the data to inform those costs. The following two scenarios describe different ways to deal with these missing values in the data depending on the objective of inference.

The known farmed land scenario represents how farmers make real-time cultivation decisions. Estimates from this scenario are based only on the parts of each landform that were planted in a given field-year. Accordingly, estimates from this scenario are generally going to be biased if the objective is to understand how the totality of a landform contributes to yield or profit because it likely represents the most machinery accessible parts of each landform and excludes more difficult to cultivate (i.e., wet during certain periods) areas. For example, data included in this scenario may only account for a small portion of a NWI temporary or seasonal wetland (i.e., only the outermost edge of a wetland during a moderately wet year). For yield and profit calculations under the "known farmed land" scenario, I left profit and yield for those grid points as "NA" for that year and consequently those grid points were not included when averaging profit or yields for the landform feature in which the grid point resided.

The all farmable land scenario is an attempt to get a better representation of yield and profit from the totality of each landform. This scenario assumes that all temporary and seasonal wetlands and sinks are farmable, at least in some years, but still excludes more permanent water bodies. It may be a better way to look at overall profitability and productivity of these landform features (e.g., wetlands, wetland margins, and sinks) in the long-term and from a land management perspective. It also may represent profitability lost or an opportunity missed if profit from cultivation is the only revenue produced from a wetland (i.e., not enrolled in a conservation program). Under the "all-farmable land" scenario, I changed profit for grid points with "NA" values from the planting raster and yield with "NA" values from harvest rasters to "0" and were included when averaging profit for the landform feature in which the grid point resided. Like the known farming scenario, I only applied direct costs to areas where there was documented planting. These methods likely underestimated direct costs for both scenarios because it does not account for any preparation work done to the area, which is often done during the preceding fall (see Chapter 2).

Analysis

I analyzed crop types (i.e., corn, soybean) separately for model interpretability. I used linear mixed-effects models with a normal distribution from the package "lme4" in program R (R Core Team 2020) to explain variation in the response variables of yield and profit for landform classes. I modeled the profit response variable on grid scale and the estimates were converted to US dollars (USD) per hectare and USD per acre. I modeled the yield response variable as bushels per acre (bu/acre) and the estimates were converted to megagrams per hectare (Mg/ha). I used the following fixed effects predictor variables in an *a priori* full model: landform, early SPEI, late SPEI, winter SPEI, UPI, and USCV as main effects and the interactions between each main effect and landform. The interactions were incorporated because landform was expected to affect variation in crop yields differently under varying levels of the other main effects. I included a nested random effect of field identity in farmer identity to account for profit variation among those groups.

I evaluated predictor variables from the *a priori* full model by comparing one-variable-removed reduced models to the full model (Arnold 2010). I evaluated the reduced models using Conditional Akaike's Information Criterion (cAIC) with the cAIC4 package (Saefken et al. 2018), which is used for evaluating fit among generalized linear mixed-effect models (Saefken et al. 2014). I considered the removed predictor variable informative if the cAIC of the reduced model was increased >2 points compared to the full model. I first evaluated all interactions and removed those that were not considered informative. If an interaction predictor variable was informative, then I included the interaction and associated main effect predictor variables in a final reduced model. Next, I assessed the main effect predictor variables not included in retained interactions with the same selection method described above. Main effects which were informative were included in the final reduced model. I compared the final reduced models to their corresponding *a priori* full and null models (i.e., null model was profit regressed against the landform category) (Burnham and Anderson 2002).

I plotted back transformed estimates and 85% confidence intervals (CI) from each model over the range of the predictor variables while holding other variables at their mean values. Any statements about landform estimate comparisons were made under the conditions that the other variables in the model were held at their mean values. I examined the results using 85% CI for all estimates because the variable selection process equates to an 85% confidence interval (Arnold 2010). I considered the model coefficient estimates for variables important if the 85% CI did not include 0. Important variables with interactions were plotted in three separate charts for ease of interpretation. Each interaction plot displayed upland estimates for a reference across that group's plots. Each of the three plots for an interaction effect grouped similar landforms together. For example, the plots on top (e.g., tagged A) included upland and temporary and seasonal wetlands, the middle plots (e.g., tagged B) included upland, dist10, dist20, and dist30 categories, and the bottom plot (e.g., tagged C) included upland, sink1, sink2, and sink3 groups. I considered model estimates for landforms different from another landform if the 85% CI did not include the point estimate of the other landform.

Results

My profit analyses included 192 and 225 field-years for corn and soybeans, respectively (Table 4.1). The yield analyses included 235 and 286 field-years for corn and soybeans, respectively (Table 3.1) and covered over 4,046 ha (10,000 acres). Crop field size ranged from 4.5–233.9 ha (11–578 acres) with a median size of 64.5 ha (159 acres). Median yields were 9.8 and 2.5 megagrams/ha (Mg/ha, (157 and 40 bu/acre)) for corn and soybeans, respectively. Temporary and seasonal wetlands had median sizes of 0.91 ha (2.25 acres) and 3.50 ha (8.65 acres), respectively.

Table 4.1. Precision agriculture yield and profitability data acquired from four producers in southeastern North Dakota, 2003–2021. Not all fields had data available for every year.

Corn Field-Years					
Farmer	**Years**	**Year Range**	**Fields**	**Profitability**	**Yield**
A	9	2011–2020	25	68	97
B	4	2010–2018	1	NA	4
C	5	2017–2021	20	39	41
D	16	2003–2018	15	85	93
Total	18		61	192	235

Soybean Field-Years					
Farmer	**Years**	**Year Range**	**Fields**	**Profitability**	**Yield**
A	9	2011–2020	25	95	103
B	7	2003–2017	1	NA	7
C	5	2017–2021	24	41	77
D	16	2003–2018	15	89	99
Total	18		65	225	286

Corn Profit — Known Farmed Land Scenario

The final model used to explain profit from corn production under the known farmed land scenario included landform, early SPEI, winter SPEI, and an interaction with landform and early SPEI (Appendix C (Tables C.1 and C.2)). Increased winter SPEI ($\hat{\beta}$ = -0.015, CI = [-0.02, -0.009]) decreased corn profit from \$702/ha CI = [\$644, \$761]) to \$554/ha CI = [\$503, \$606]) from lowest (-1.75) to highest (2.25) SPEI observed (Figure 4.1, Appendix C (Table C.4)).

The relationship between corn profit from known farmed land and early SPEI varied by landform. Profit in uplands >30 m, between 20-30 m, and between 10-20 m from wetlands was relatively invariant to variation in early SPEI ($\hat{\beta}_{upland}$ = 0.005, CI = [-0.011, 0.022]; $\hat{\beta}_{dist30}$ = -0.002, CI = [-0.019, 0.015]; $\hat{\beta}_{dist20}$ = -0.01, CI = [-0.027, 0.007]) and decreased in upland areas <10 m from wetlands, in sinks, and in wetlands ($\hat{\beta}_{dist10}$ = -0.02, CI = [-0.036, -0.003]; $\hat{\beta}_{sink1}$ = -0.043, CI = [-0.06, -0.027]; $\hat{\beta}_{sink2}$ = -0.073, CI = [-0.09, -0.056]; $\hat{\beta}_{sink3}$ = -0.079, CI = [-0.098, -0.059]; $\hat{\beta}_{temp}$ = -0.066, CI = [-0.084, -0.048]; $\hat{\beta}_{seasonal}$ = -0.053, CI = [-0.07, -0.035]; Figure 4.2, Appendix C (Table C.4)). Cultivated portions of temporary wetlands had slightly higher profit estimates (\$813/ha, CI=[\$721, \$905]), whereas seasonal wetlands had similar profits estimates (\$697/ha, CI=[\$595, \$798]) compared to uplands (\$756/ha, CI = [\$661, \$852]) for low SPEI values, but profits were below the total-cost profit 0 line (breakeven) for high SPEI values (Figure 4.2). During average early SPEI conditions, corn profit from cultivated portions of temporary wetlands was \$248/ha (32%) less than upland areas and \$215/ha above the total-cost breakeven line. Seasonal wetlands realized \$350/ha (45%) less than uplands and \$132/ha above the total cost breakeven line. Uplands within 30 m of wetlands remained profitable in relation to total-cost profit.

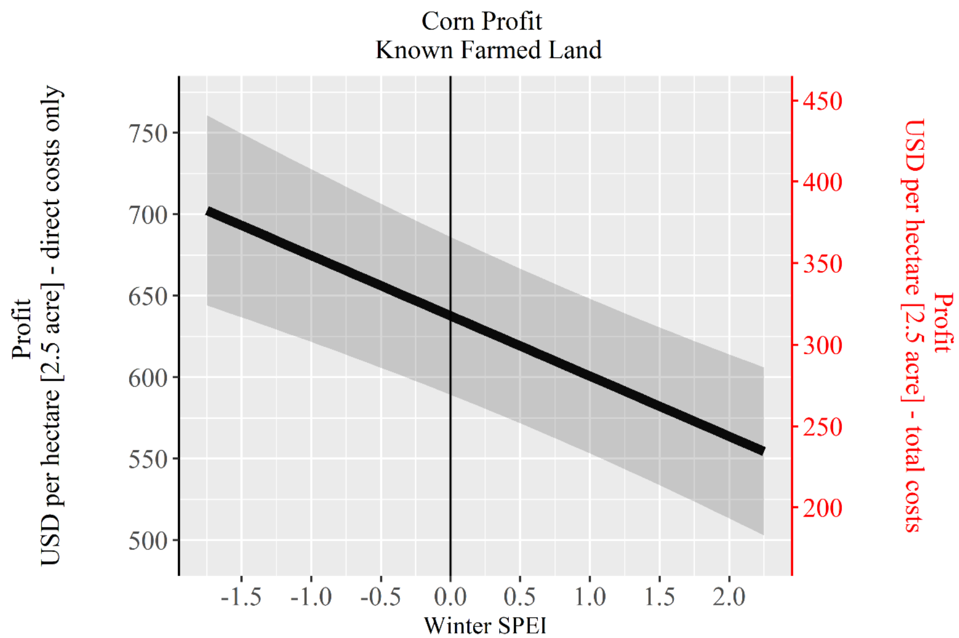

Figure 4.2. Corn profit estimates with 85% confidence limits in relation to winter SPEI from the known farmed land scenario. Estimates were averaged over all landforms while other variables were held at their average. The left y-axis depicts profit in USD per hectare (2.5 acre) when profit is calculated with only direct costs. The right y-axis depicts profit in USD per hectare (2.5 acre) when profit is adjusted for total cost (i.e., includes direct and indirect costs). The vertical line depicts the long-term average SPEI.

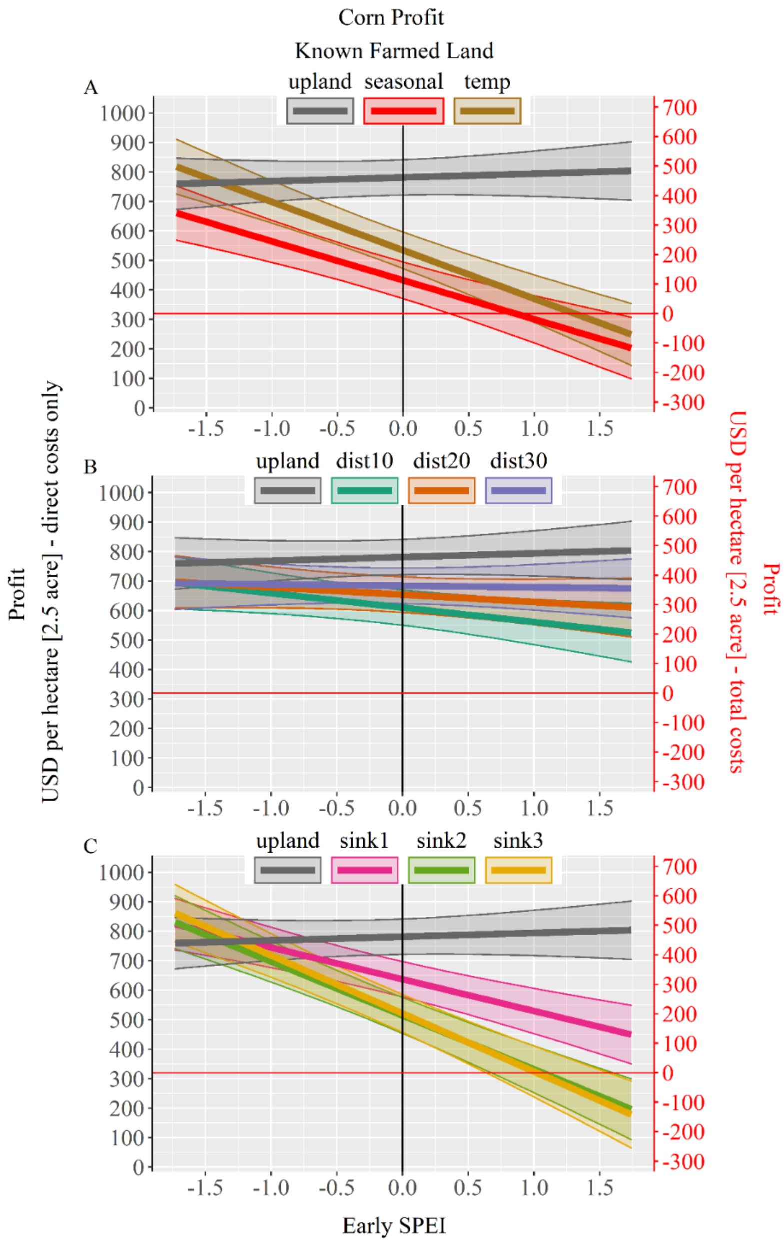

Figure 4.3. Corn profit estimates with 85% confidence limits in relation to early SPEI for the nine landform categories from the known farmed land scenario. The left y-axis depicts profit in USD per hectare (2.5 acre) when profit is calculated with only direct costs. The right y-axis depicts profit in USD per hectare (2.5 acre) when profit is adjusted for total cost (i.e., includes direct and indirect costs). The horizontal black line depicts the '0' profit or breakeven line when only direct costs are included in profit calculations. The horizontal red line depicts the '0' profit or breakeven line when total costs are included in profit calculations. The vertical line depicts the long-term average SPEI. A – Corn profit estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn profit estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn profit estimates for landform classes upland, sink1, sink2, and sink3.

Corn Profit — All Farmable Land Scenario

The relationship between corn profit from the all farmable land scenario and early SPEI, winter SPEI, and UPI varied by landform (Appendix C (Tables C.1 and C.2)). Increased winter SPEI decreased profit for corn in all other landforms except uplands ($\hat{\beta}_{\text{upland}}$ = -0.006, CI = [-0.016, 0.004]; $\hat{\beta}_{\text{dist30}}$ = -0.016, CI = [-0.027, -0.006]; $\hat{\beta}_{\text{dist20}}$ = -0.02, CI = [-0.03, -0.01]; $\hat{\beta}_{\text{dist10}}$ = -0.024, CI = [-0.034, -0.014]; $\hat{\beta}_{\text{sink1}}$ = -0.035, CI = [-0.045, -0.025]; $\hat{\beta}_{\text{sink2}}$ = -0.054, CI = [-0.064, -0.044]; $\hat{\beta}_{\text{sink3}}$ = -0.041, CI = [-0.052, -0.031]; $\hat{\beta}_{\text{temp}}$ = -0.039, CI = [-0.049, -0.028]; $\hat{\beta}_{\text{seasonal}}$ = -0.034, CI = [-0.045, -0.024]; Figure 4.4, Appendix C (Table C.5)). Profit estimates for seasonal wetlands reached the total-cost breakeven line at less than average winter SPEI values (≥-0.40, Figure 4.4). Profits estimates for temporary wetlands fell below total-cost breakeven when winter SPEI values were ≥ 0.78.

As early SPEI increased in the all farmable land scenario, upland corn profit increased ($\hat{\beta}_{\text{upland}}$ = 0.018, CI = [0.005, 0.03]) while temporary, seasonal, and all sink groups decreased in profit ($\hat{\beta}_{\text{temp}}$ = -0.052, CI = [-0.065, -0.039]; $\hat{\beta}_{\text{seasonal}}$ = -0.033, CI = [-0.045, -0.02]; $\hat{\beta}_{\text{sink1}}$ = -0.029, CI = [-0.041, -0.016]; $\hat{\beta}_{\text{sink2}}$ = -0.046, CI = [-0.059, -0.034]; $\hat{\beta}_{\text{sink3}}$ = -0.026, CI = [-0.039, -0.013]; Figure 4.5, Appendix C (Table C.5)). Profit in areas between wetland boundaries and <30 m into the uplands were invariant to early SPEI ($\hat{\beta}_{\text{dist10}}$ = -0.012, CI = [-0.024, 0.001]; $\hat{\beta}_{\text{dist20}}$ = -0.001, CI = [-0.013, 0.012]; $\hat{\beta}_{\text{dist30}}$ = 0.006, CI = [-0.007, 0.018]; Figure 4.5, Appendix C (Table C.5)). Confidence intervals for profit from seasonal wetlands overlapped or fell below total-cost breakeven regardless of early SPEI. Profit estimates for seasonal wetlands ($224/ha CI = [$169, $278]) at average early SPEI were $517/ha (70%) less than upland area estimates ($741/ha CI = [$687, $794]). Corn profit estimates for temporary wetlands fell below total-cost breakeven at an early SPEI of about 0.08 and only profited about $11/ha on an average early

SPEI when accounting for total costs. Corn profit estimates from temporary wetlands ($331/ha CI = [$277, $386]) were approximately $410/ha (55%) less than upland areas at average early SPEI. Corn profit from sink2 and sink3 were similar to temporary wetlands and were below total-cost profit breakeven as early SPEI increased. Corn profit from sink1 areas had its lower confidence limit overlap the total-cost break-even at the highest levels of early SPEI.

Profit estimates from all landforms were invariant to variation in UPI ($\hat{\beta}_{\text{upland}}$ = 0.273, CI = [-0.055, 0.601]; $\hat{\beta}_{\text{dist30}}$ = 0.319, CI = [-0.01, 0.647]; $\hat{\beta}_{\text{dist20}}$ = 0.155, CI = [-0.174, 0.484]; $\hat{\beta}_{\text{dist10}}$ = 0.05, CI = [-0.278, 0.378]; $\hat{\beta}_{\text{sink1}}$ = 0.003, CI = [-0.325, 0.331]; $\hat{\beta}_{\text{sink2}}$ = -0.284, CI = [-0.62, 0.053]; $\hat{\beta}_{\text{sink3}}$ = -0.266, CI = [-0.603, 0.072]; $\hat{\beta}_{\text{temp}}$ = 0.286, CI = [-0.046, 0.618]; $\hat{\beta}_{\text{seasonal}}$ = -0.052, CI = [-0.39, 0.287]; Appendix C (Table C.5)).

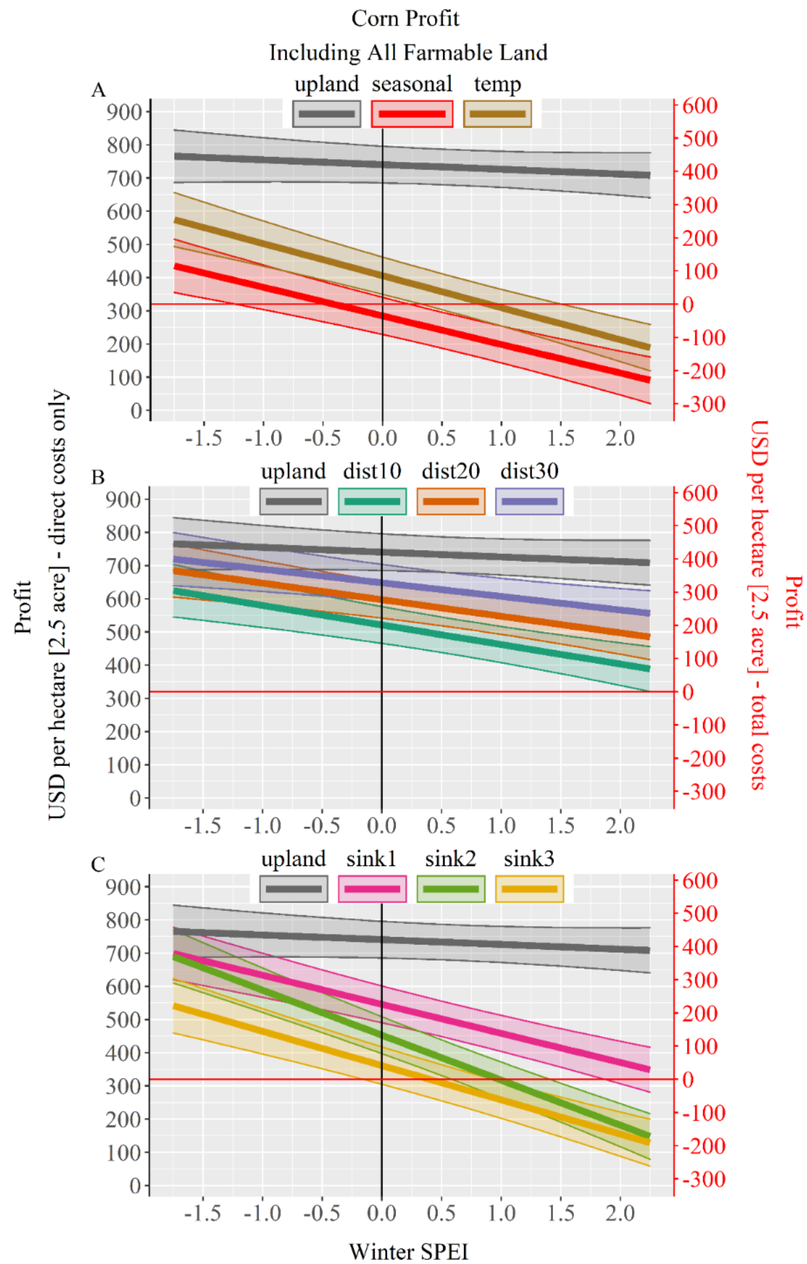

Figure 4.4. Corn profit estimates with 85% confidence limits in relation to winter SPEI for the nine landform categories from the all farmable land scenario. The left y-axis depicts profit in USD per hectare (2.5 acre) when profit is calculated with only direct costs. The right y-axis depicts profit in USD per acre (0.4 ha) when profit is adjusted for total cost (i.e., includes direct and indirect costs). The horizontal black line depicts the '0' profit or breakeven line when only direct costs are included in profit calculations. The horizontal red line depicts the '0' profit or breakeven line when total costs are included in profit calculations. The vertical line depicts the long-term average SPEI. A – Corn profit estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn profit estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn profit estimates for landform classes upland, sink1, sink2, and sink3.

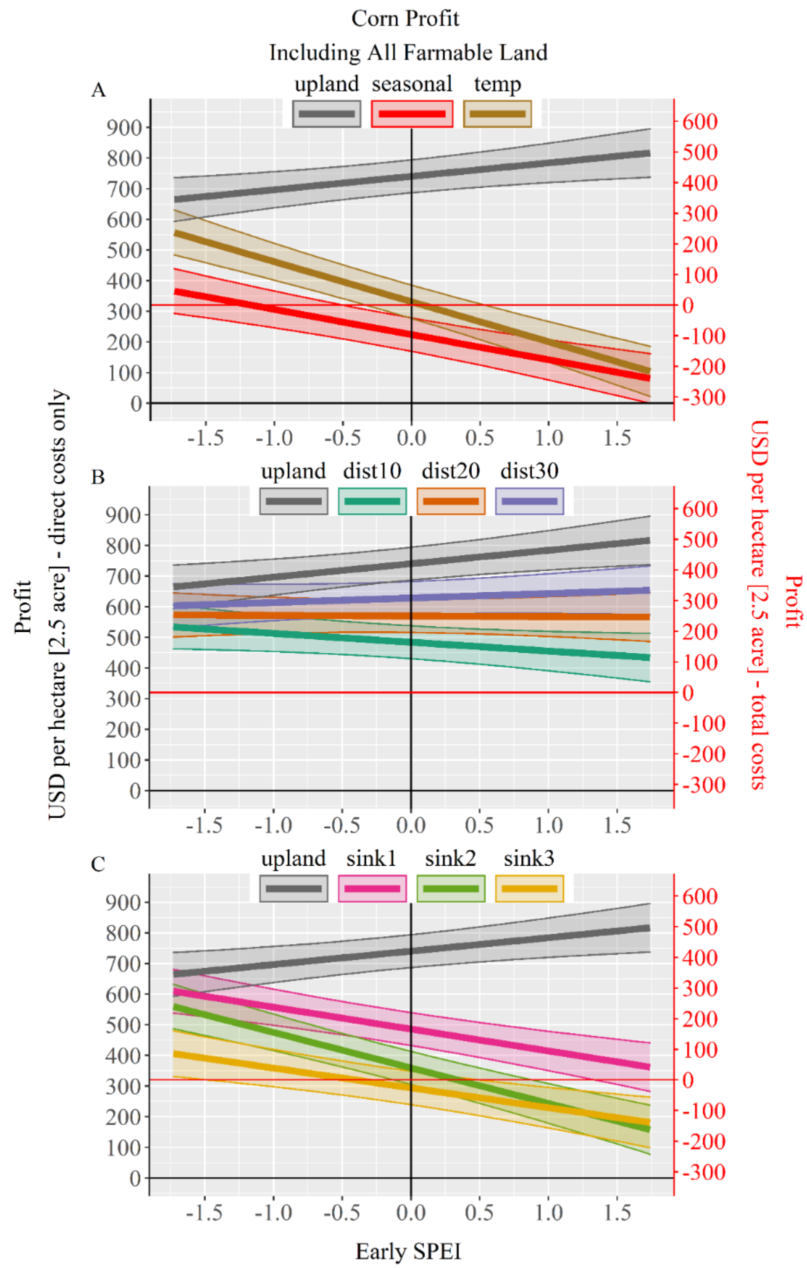

Figure 4.5. Corn profit estimates with 85% confidence limits in relation to early SPEI for the nine landform categories from the all farmable land scenario. The left y-axis depicts profit in USD per hectare (2.5 acre) when profit is calculated with only direct costs. The right y-axis depicts profit in USD per hectare (2.5 acre) when profit is adjusted for total cost (i.e., includes direct and indirect costs). The horizontal black line depicts the ‘0’ profit or breakeven line when only direct costs are included in profit calculations. The horizontal red line depicts the ‘0’ profit or breakeven line when total costs are included in profit calculations. The vertical line depicts the long-term average SPEI. A – Corn profit estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn profit estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn profit estimates for landform classes upland, sink1, sink2, and sink3.

Corn Yield — Known Farmed Land Scenario

The final model used to explain corn yield under the known farmed land scenario contained predictor variables including landform, late SPEI, early SPEI, winter SPEI, USCV and interactions with landform for early SPEI, winter SPEI, and USCV predictor variables (Appendix C (Tables C.1 and C.2)). Estimates of corn yield from the known planted areas increased as late SPEI increased ($\hat{\beta}$ = 6.405, CI = [5.212, 7.597]; Figure 4.6, Appendix C (Table C.6)).

Corn yield in uplands areas was invariant to variation in early SPEI ($\hat{\beta}_{upland}$ = -2.364, CI = [-5.772, 1.043]; Figure 4.7). Corn yield for cultivated portions of areas within 30 m of wetlands, sink1, sink2, sink3, and temporary and seasonal wetlands decreased as early SPEI increased ($\hat{\beta}_{dist30}$ = -3.619, CI = [-7.113, -0.125]); $\hat{\beta}_{dist20}$ = -5.715, CI = [-9.209, -2.221]); $\hat{\beta}_{dist10}$ = -7.873, CI = [-11.322, -4.424]; $\hat{\beta}_{sink1}$ = -15.638, CI = [-19.051, -12.225]; $\hat{\beta}_{sink2}$ = -20.809, CI = [-24.381, -17.237]; $\hat{\beta}_{sink3}$ = -19.152, CI = [-23.24, -15.064]; $\hat{\beta}_{temp}$ = -16.54, CI = [-20.234, -12.847]; $\hat{\beta}_{seasonal}$ = -16.752, CI = [-20.434, -13.07]; Figure 4.7, Appendix C (Table C.6)). Corn yield estimates from cultivated portions of temporary wetlands (11.1 Mg/ha CI = [10.5, 11.6]) were similar to that of uplands (10.9 Mg/ha CI = [10.4, 11.4]) at the lowest early SPEI values (-1.7) but were considerably less (2.9 Mg/ha, 29%) at high early SPEI values (1.7, temporary 7.5 Mg/ha CI = [7, 8.1]; upland 10.4 Mg/ha CI = [9.8, 10.9]). Corn yield estimates from cultivated portions of seasonal wetlands were lower across the observed range of early SPEI and were about 2.4 Mg/ha (23%) less with average early SPEI (seasonal 8.2 Mg/ha CI = [7.8—8.5]; upland 10.6 Mg/ha CI = [10.3, 11])

Corn yield from upland and areas between 20–30 m from wetlands were invariant to variation in winter SPEI ($\hat{\beta}_{upland}$ = 0.094, CI = [-2.75, 2.939]; $\hat{\beta}_{dist30}$ = -2.421, CI = [-5.333, 0.491]; Figure 4.8). Yield from all other landforms decreased with increasing winter SPEI values ($\hat{\beta}_{dist20}$ = -3.052, CI = [-5.964, -0.14]; $\hat{\beta}_{dist10}$ = -4.654, CI = [-7.537, -1.771]; $\hat{\beta}_{sink1}$ = -5.093, CI = [-7.951, -2.236]; $\hat{\beta}_{sink2}$ = -8.938, CI = [-11.892, -5.984]; $\hat{\beta}_{sink3}$ = -6.351, CI = [-9.757, -2.944]; $\hat{\beta}_{temp}$ = -9.041, CI = [-12.092, -5.991]; $\hat{\beta}_{seasonal}$ = -10.153, CI = [-13.231, -7.075]; Appendix C (Table C.6)). Corn yield estimates from cultivated portions of temporary wetlands (10.7 Mg/ha CI = [10.1, 11.3]) were similar to that of uplands (10.6 Mg/ha CI = [10.1, 11.2]) at the low SPEI values (-1.75) but were considerably less (21%) at high winter SPEI values (2.25, temporary 8.4 Mg/ha CI = [7.9, 8.9]; upland 10.6 Mg/ha CI = [10.2, 11.1]). Corn yield estimates from cultivated portions of seasonal wetlands were lower across the observed range of winter SPEI and were about 2 Mg/ha (19%) less with average winter SPEI (seasonal 8.6 Mg/ha CI = [8.2, 9]; upland 10.6 Mg/ha CI = [10.3, 11]).

Corn yields for uplands, 20–30 m from wetlands, and sink1 were unaffected by variation in USCV ($\hat{\beta}_{upland}$ = 31.11, CI = [-12.691, 74.912]; $\hat{\beta}_{dist20}$ = 38.843, CI = [-5.544, 83.229]; $\hat{\beta}_{sink1}$ = 9.826, CI = [-33.999, 53.651]; Figure 4.9). Corn yields for cultivated portions of dist10, dist30, temporary wetlands, and seasonal wetlands increased as USCV increased (i.e., flatter terrain, $\hat{\beta}_{dist10}$ = 48.832, CI = [4.742, 92.922]; $\hat{\beta}_{dist30}$ = 50.707, CI = [6.32, 95.094]; $\hat{\beta}_{temp}$ = 57.449, CI = [12.072, 102.826]; $\hat{\beta}_{seasonal}$ = 52.24, CI = [3.827, 100.654]) while yield from cultivated portions of sink2 and sink3 decreased ($\hat{\beta}_{sink2}$ = -47.586, CI = [-92.051, -3.122]; $\hat{\beta}_{sink3}$ = -63.18, CI = [-110.093, -16.267]).

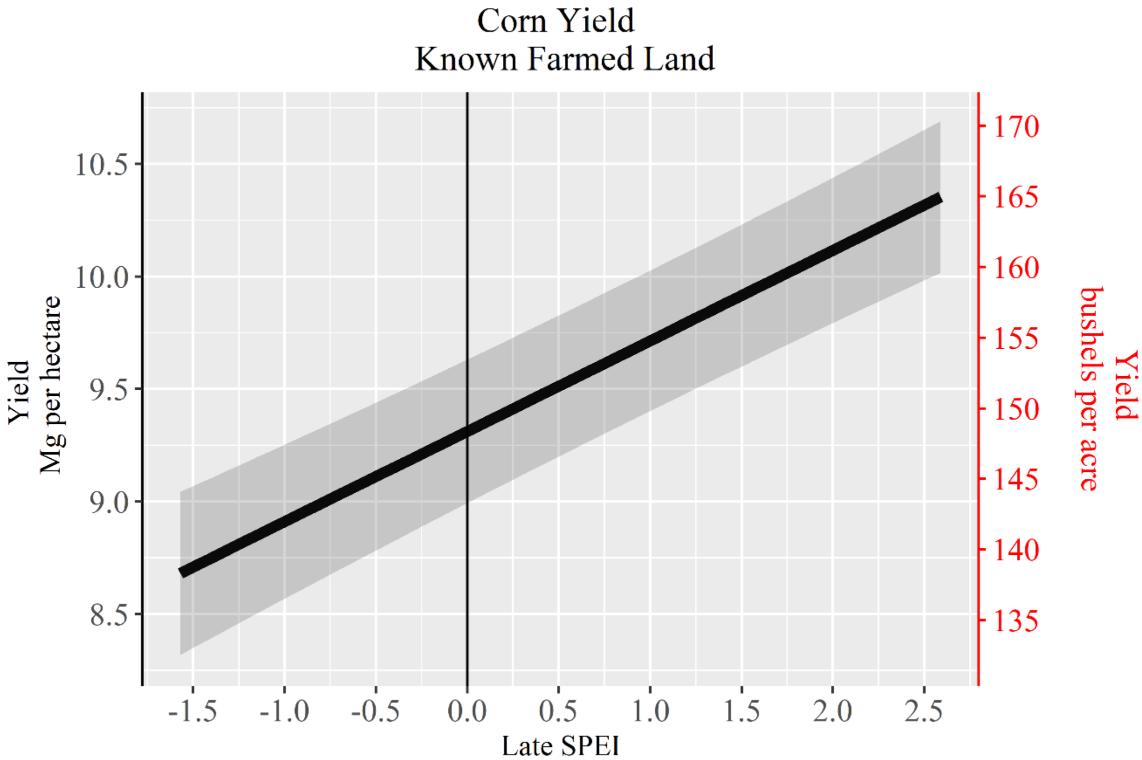

Figure 4.6. Corn yield estimates with 85% confidence limits in relation to late SPEI from the known farmed land scenario. Estimates were averaged over all landforms while other variables were held at their average. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. The vertical line depicts the long-term average SPEI.

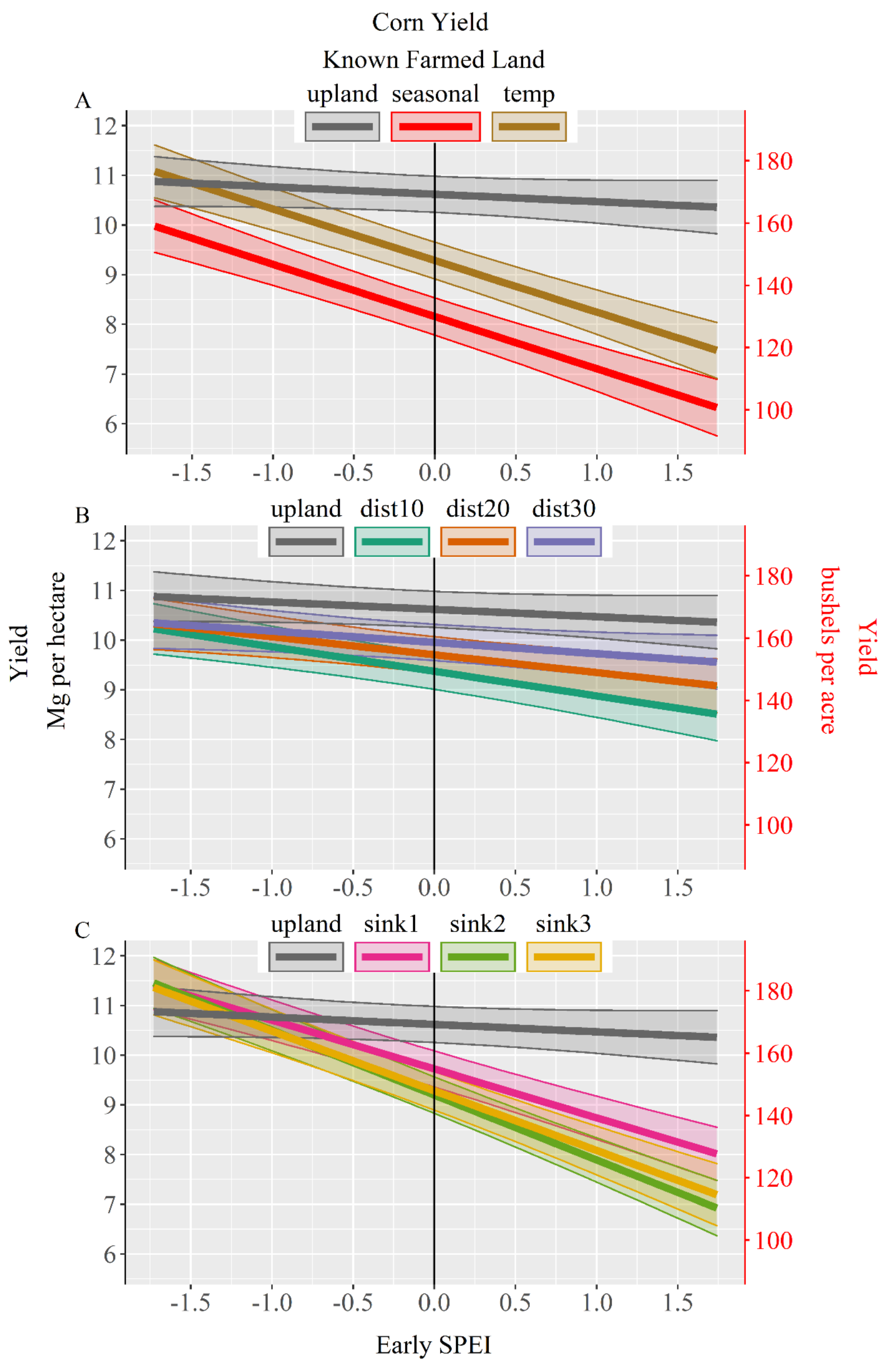

Figure 4.7. Corn yield estimates with 85% confidence limits in relation to early SPEI for the nine landform categories from the known farmed land scenario. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. The vertical line depicts the long-term average SPEI. A – Corn yield estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn yield estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn yield estimates for landform classes upland, sink1, sink2, and sink3.

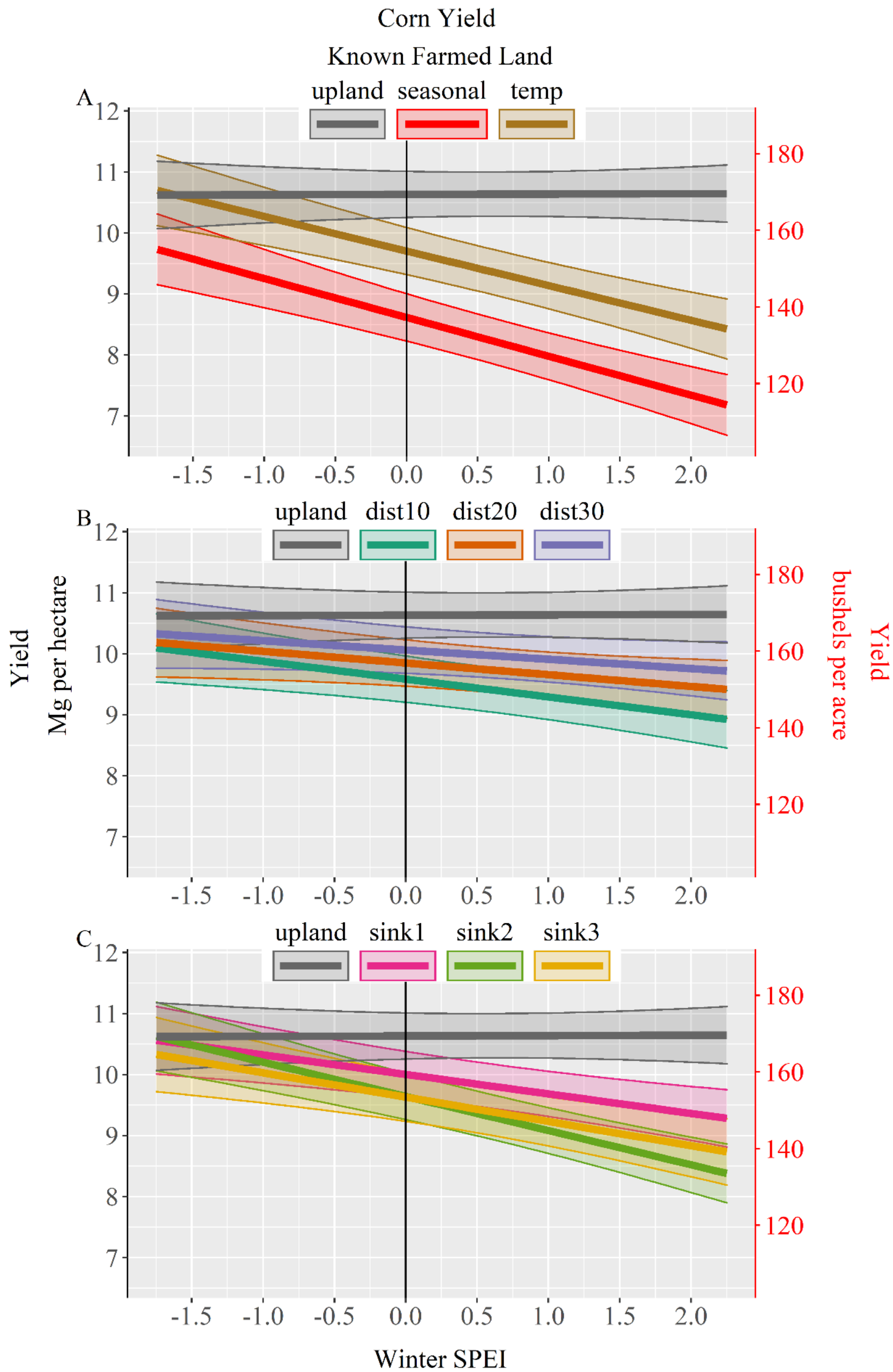

Figure 4.8. Corn yield estimates with 85% confidence limits in relation to winter SPEI for the nine landform categories from the known farmed land scenario. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. The vertical line depicts the long-term average SPEI. A – Corn yield estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn yield estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn yield estimates for landform classes upland, sink1, sink2, and sink3.

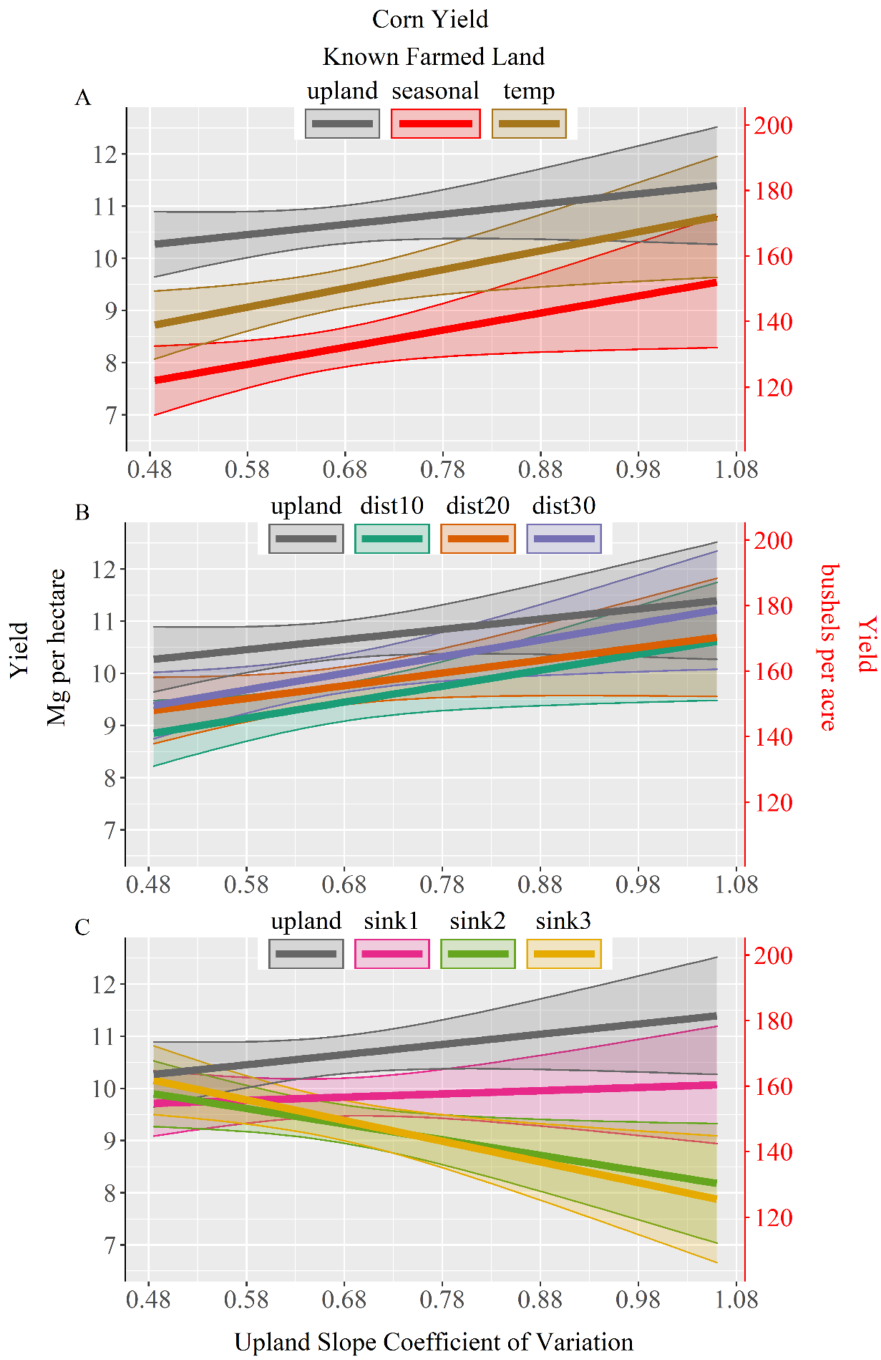

Figure 4.9. Corn yield estimates with 85% confidence limits in relation to Upland Slope Coefficient of Variation (USCV) for the nine landform categories from the known farmed land scenario. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. A – Corn yield estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn yield estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn yield estimates for landform classes upland, sink1, sink2, and sink3.

Corn Yield — All Farmable Land Scenario

The final model used to explain corn yield under the all farmable land scenario contained predictor variables including landform, late SPEI, early SPEI, winter SPEI, USCV, UPI and interactions with landform for early SPEI, winter SPEI, USCV, and UPI predictor variables (Appendix C (Tables C.1 and C.2)). Overall corn yield increased as late SPEI increased ($\hat{\beta}$ = 9.056, CI = [7.564, 10.548]; Figure 4.10, Appendix C (Table C.7)).

Overall corn yield from uplands, dist30, dist20, and dist10 were relatively unaffected by variation in early SPEI ($\hat{\beta}_{upland}$ = 1.087, CI = [-3.268, 5.442]; $\hat{\beta}_{dist30}$ = 0.585, CI = [-3.827, 4.997]; $\hat{\beta}_{dist20}$ = -0.994, CI = [-5.406, 3.419]; $\hat{\beta}_{dist10}$ = -2.169, CI = [-6.527, 2.19]; Figure 4.11). Overall corn yield for sink1, sink2, sink3, and temporary and seasonal wetlands decreased with increasing early SPEI ($\hat{\beta}_{sink1}$ = -11.515, CI = [-15.868, -7.162]; $\hat{\beta}_{sink2}$ = -17.406, CI = [-21.849, -12.964]; $\hat{\beta}_{sink3}$ = -9.082, CI = [-13.757, -4.407]; $\hat{\beta}_{temp}$ = -14.377, CI = [-18.929, -9.826]; $\hat{\beta}_{seasonal}$ = -10.524, CI = [-15.043, -6.005]). Overall corn yield estimates from temporary wetlands (5.6 Mg/ha CI = [5.1, 6.1]) were 4.7 Mg/ha (42%) lower than uplands (9.7 Mg/ha CI = [9.2, 10.2]) at average early SPEI. Overall corn yield estimates from seasonal wetlands (3.5 Mg/ha CI = [3, 4]) were 6.2 Mg/ha (64%) less than upland yield estimates at average early SPEI.

Overall corn yield estimates for all landforms decreased as winter SPEI increased ($\hat{\beta}_{upland}$ = -4.619, CI = [-8.287, -0.95]; $\hat{\beta}_{dist30}$ = -7.292, CI = [-11.013, -3.572]; $\hat{\beta}_{dist20}$ = -8.873, CI = [-12.594, -5.152]; $\hat{\beta}_{dist10}$ = -10.396, CI = [-14.07, -6.722]; $\hat{\beta}_{sink1}$ = -16.921, CI = [-20.593, -13.249]; $\hat{\beta}_{sink2}$ = -23.535, CI = [-27.277, -19.793]; $\hat{\beta}_{sink3}$ = -21.139, CI = [-25.082, -17.196]; $\hat{\beta}_{temp}$ = -17.608, CI = [-21.45, -13.766]; $\hat{\beta}_{seasonal}$ = -13.53, CI = [-17.344, -9.717]; Figure 4.12, Appendix C (Table C.7)). Overall corn yield estimates from temporary and seasonal wetlands were 3.5 Mg/ha (36%) and 4.8 Mg/ha (59%) less than uplands, respectively, at average winter

SPEI (temporary 6.3 Mg/ha CI = [5.8, 6.9]; seasonal 4 Mg/ha CI = [3.5, 4.6]; upland 9.8 Mg/ha CI = [9.3, 10.3]) and were lower than upland estimates across the range of winter SPEI.

Overall corn yields for all landforms, except temporary wetlands, were invariant to variation in UPI ($\hat{\beta}_{\text{upland}}$ = 81.809, CI = [-41.041, 204.658]; $\hat{\beta}_{\text{dist30}}$ = 84.382, CI = [-38.564, 207.328]; $\hat{\beta}_{\text{dist20}}$ = 32.157, CI = [-90.792, 155.105]; $\hat{\beta}_{\text{dist10}}$ = -9.55, CI = [-132.447, 113.346]; $\hat{\beta}_{\text{sink1}}$ = 27.068, CI = [-95.79, 149.926]; $\hat{\beta}_{\text{sink2}}$ = -86.341, CI = [-211.04, 38.358]; $\hat{\beta}_{\text{sink3}}$ = -95.664, CI = [-222.756, 31.428]; $\hat{\beta}_{\text{seasonal}}$ = 54.146, CI = [-71.413, 179.704]; Figure 4.13, Appendix C (Table C.7)). Overall corn yield from temporary wetlands ($\hat{\beta}_{\text{temp}}$ = 149.318, CI = [25.765, 272.87]) increased as UPI increased.

Overall corn yields for uplands, dist30, dist20, dist10, temporary wetlands, and seasonal wetlands increased as USCV increased ($\hat{\beta}_{\text{upland}}$ = 67.576, CI = [5.589, 129.563]; $\hat{\beta}_{\text{dist30}}$ = 90.511, CI = [28.119, 152.903]; $\hat{\beta}_{\text{dist20}}$ = 98.242, CI = [35.85, 160.634]; $\hat{\beta}_{\text{dist10}}$ = -9.55, CI = [-132.447, 113.346]; $\hat{\beta}_{\text{temp}}$ = 149.318, CI = [25.765, 272.87]; $\hat{\beta}_{\text{seasonal}}$ = 54.146, CI = [-71.413, 179.704]; Figure 4.14, Appendix C (Table C.7)). Overall corn yields for sink1, sink2, and sink3 were unaffected by variation in USCV ($\hat{\beta}_{\text{sink2}}$ = -86.341, CI = [-211.04, 38.358]; $\hat{\beta}_{\text{sink2}}$ = -86.341, CI = [-211.04, 38.358]; $\hat{\beta}_{\text{sink3}}$ = -95.664, CI = [-222.756, 31.428]; Figure 4.14).

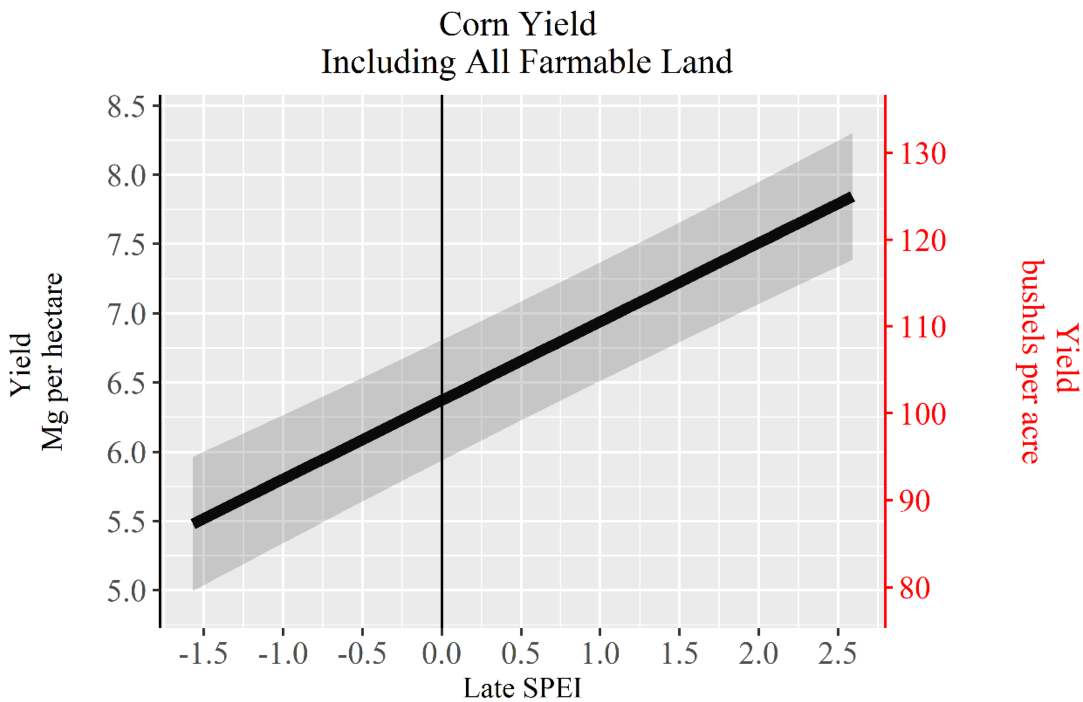

Figure 4.10. Corn yield estimates with 85% confidence limits in relation to late SPEI from the all farmable land scenario. Estimates were averaged over all landforms while other variables were held at their average. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. The vertical line depicts the long-term average SPEI.

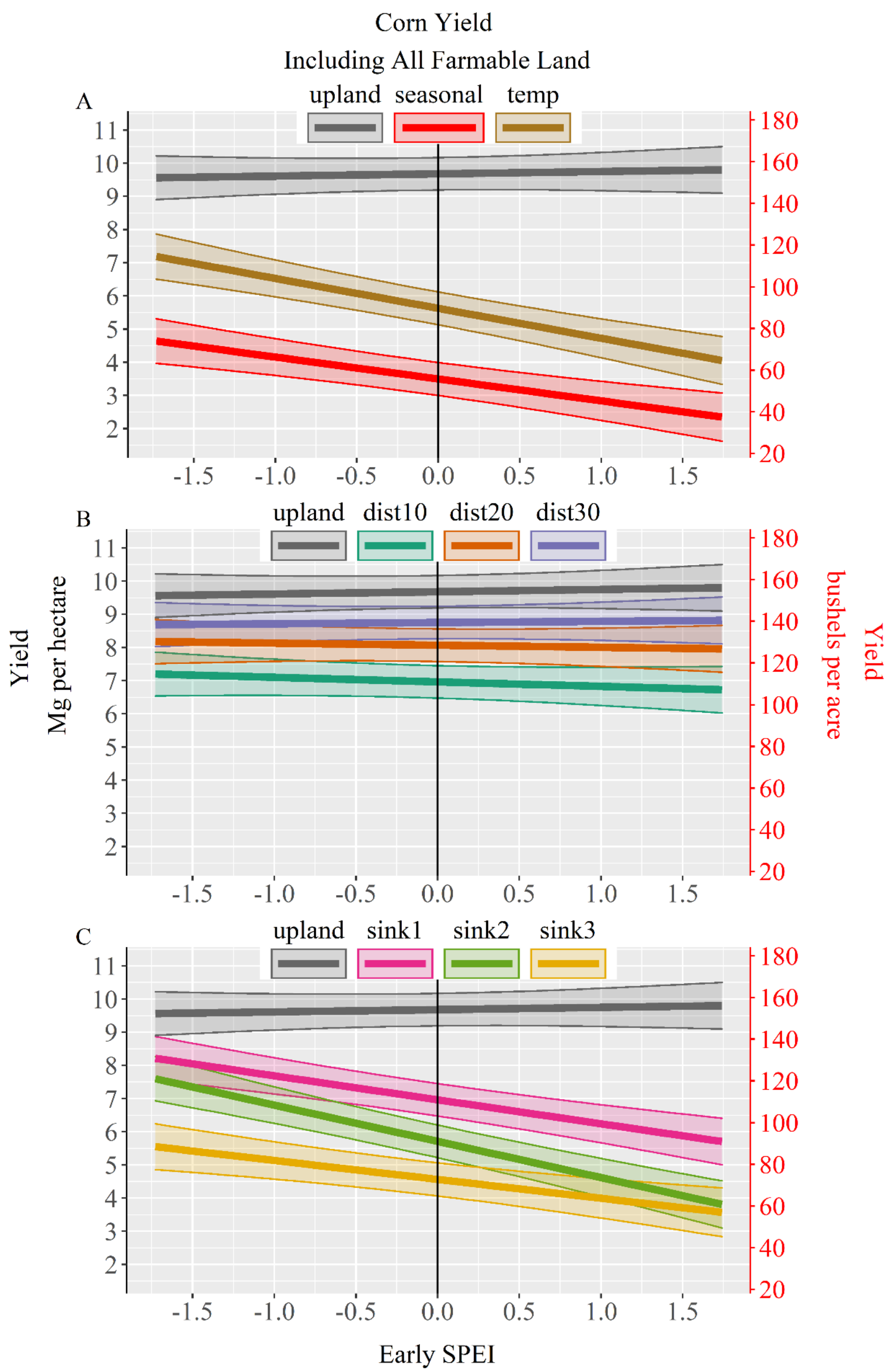

Figure 4.11. Corn yield estimates with 85% confidence limits in relation to early SPEI for the nine landform categories from the all farmable land scenario. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. The vertical line depicts the long-term average SPEI. A – Corn yield estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn yield estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn yield estimates for landform classes upland, sink1, sink2, and sink3.

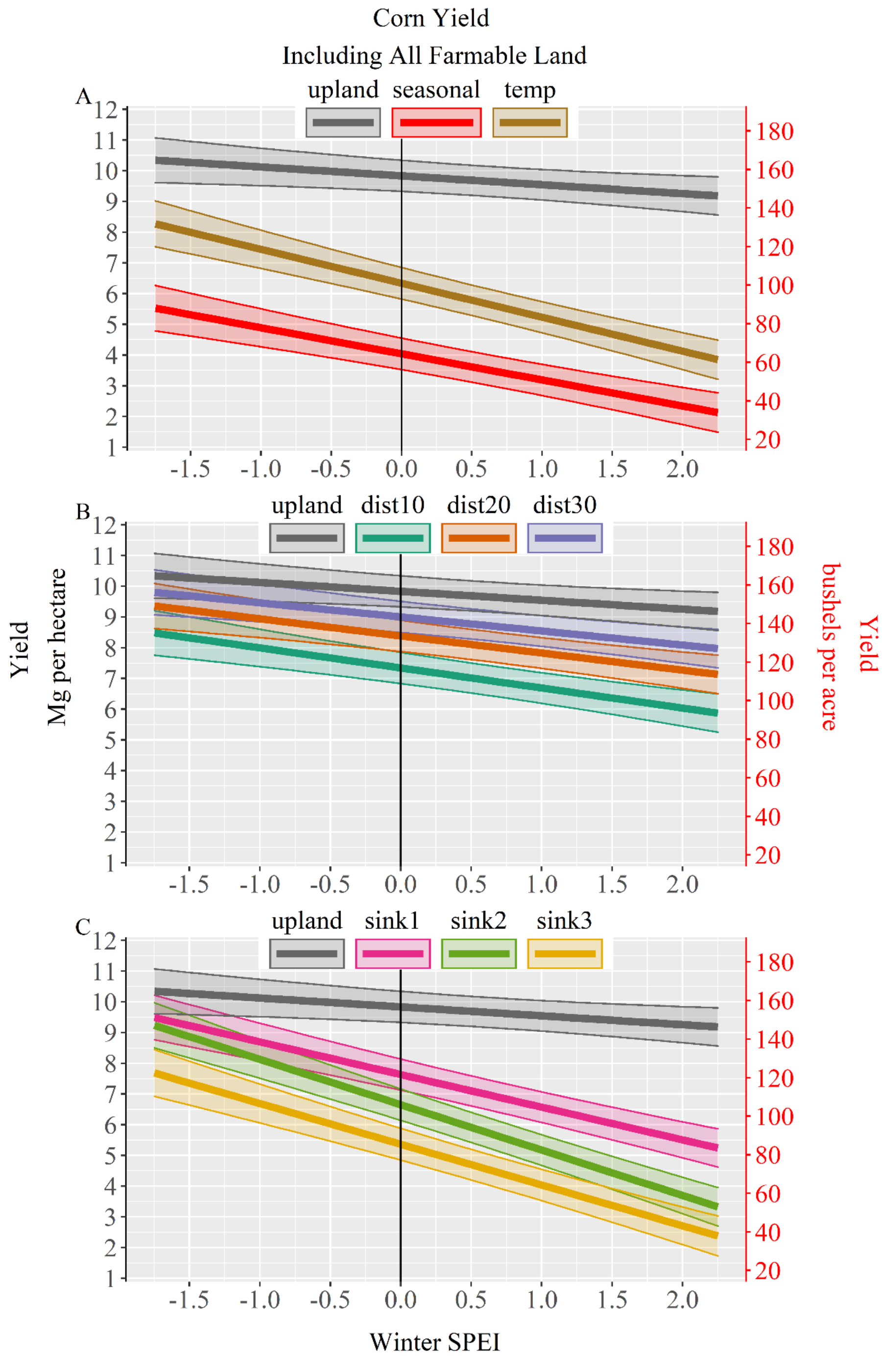

Figure 4.12. Corn yield estimates with 85% confidence limits in relation to winter SPEI for the nine landform categories from the all farmable land scenario. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. The vertical line depicts the long-term average SPEI. A – Corn yield estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn yield estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn yield estimates for landform classes upland, sink1, sink2, and sink3.

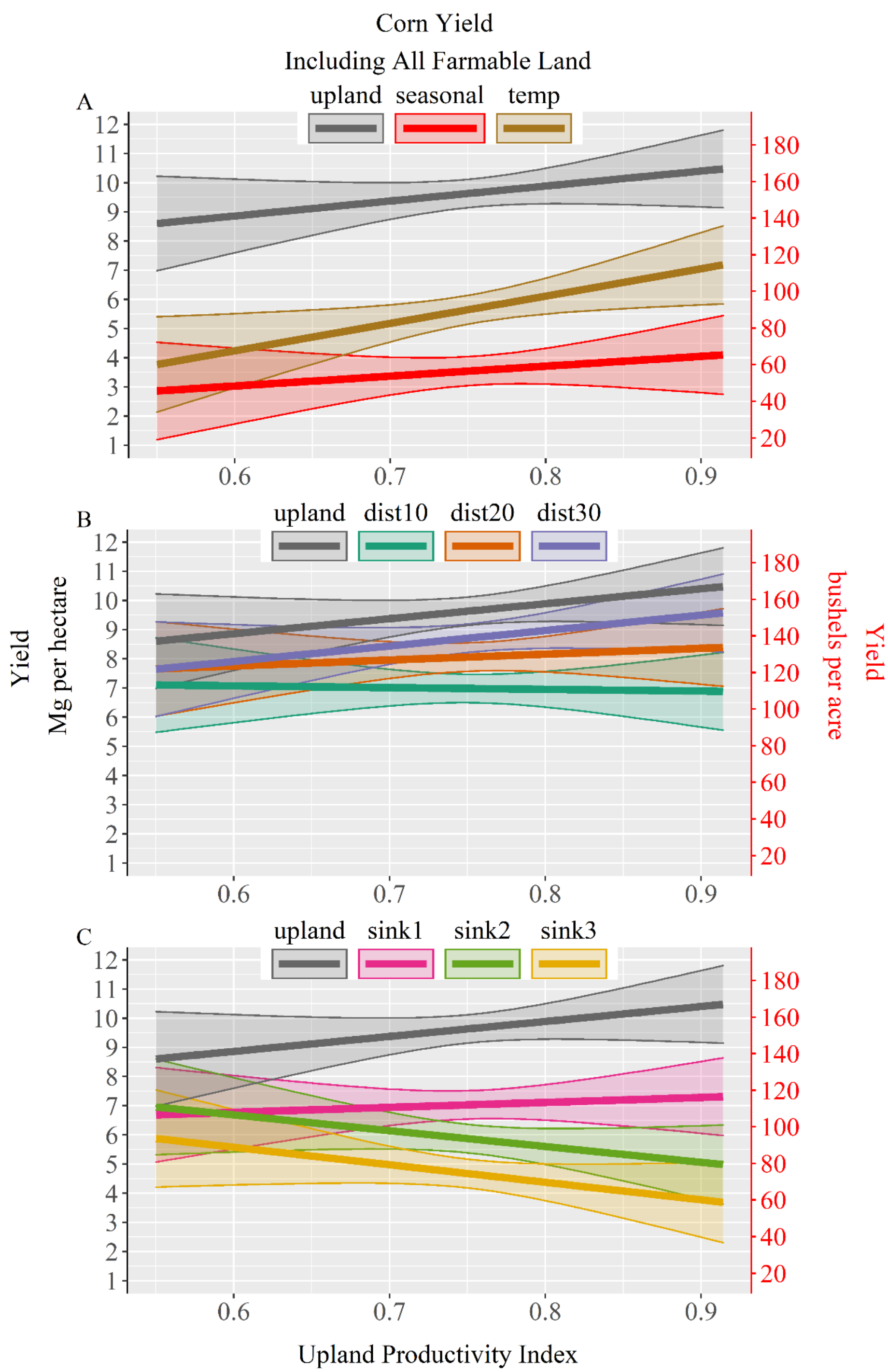

Figure 4.13. Corn yield estimates with 85% confidence limits in relation to Upland Productivity Index (UPI) for the nine landform categories from the all farmable land scenario. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. A – Corn yield estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn yield estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn yield estimates for landform classes upland, sink1, sink2, and sink3.

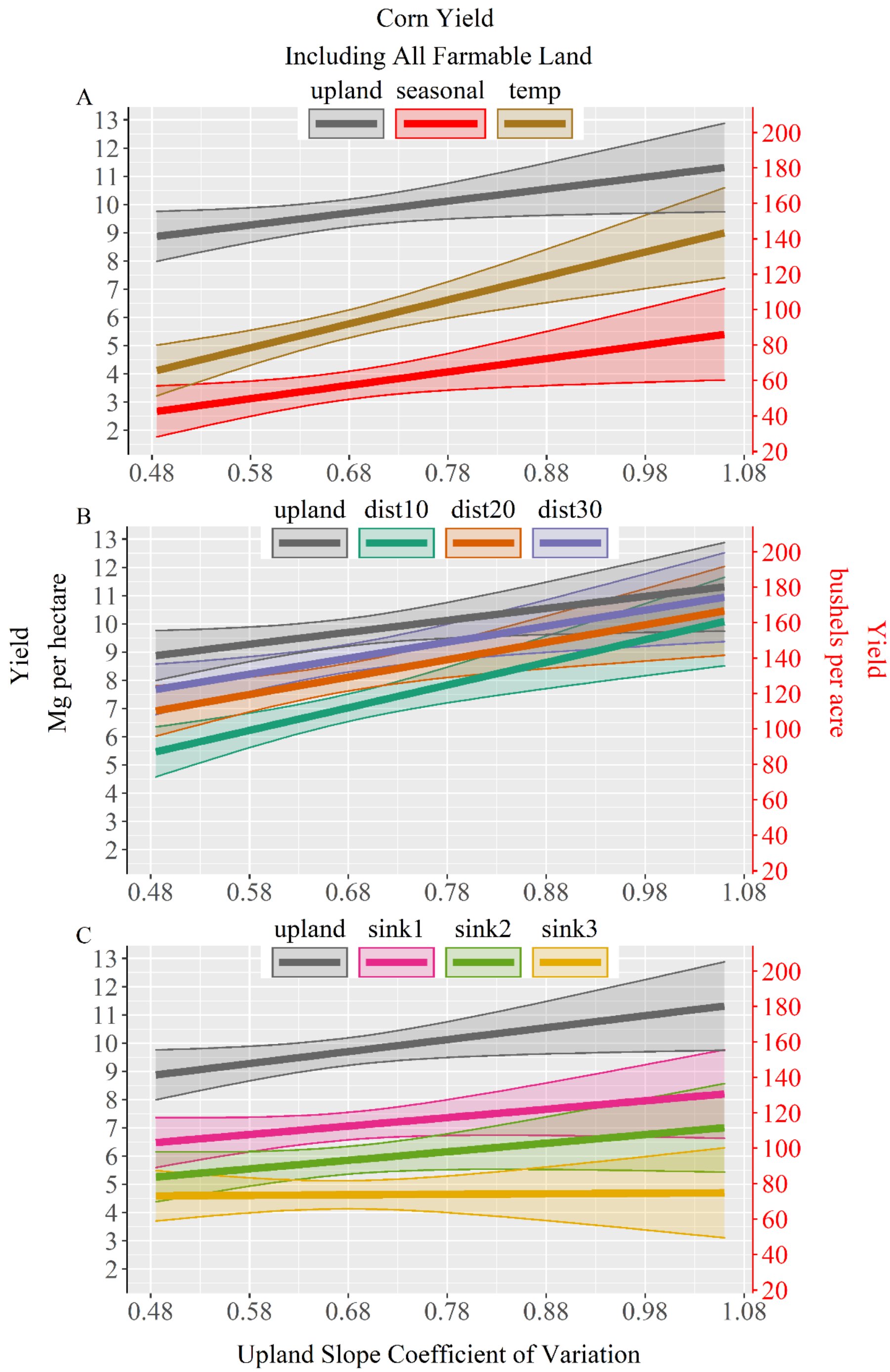

Figure 4.14. Corn yield estimates with 85% confidence limits in relation to Upland Slope Coefficient of Variation (USCV) for the nine landform categories from the all farmable land scenario. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. A – Corn yield estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn yield estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn yield estimates for landform classes upland, sink1, sink2, and sink3.

Soybean Profit — Known Farmed Land Scenario

The final model used to explain soybean profit under the known farmed land scenario contained predictor variables including landform, late SPEI, early SPEI, USCV, and an interaction of landform with early SPEI and with USCV (Appendix C (Tables C.1 and C.2)). Increased late SPEI, decreased soybean profit but remained above the total-cost profit breakeven line across the range of late SPEI ($\hat{\beta}_{lateSPEI}$ = -0.036, CI = [-0.039, -0.032]; Figure 4.15, Appendix C (Table C.8)).

Soybean profit from of uplands increased with increasing early SPEI ($\hat{\beta}_{upland}$ = 0.027, CI = [0.016, 0.038]; Figure 4.16, Appendix C (Table C.8)). Soybean profit from cultivated portions of dist30, dist20, sink2, sink3, and temporary and seasonal wetlands decreased with increasing early SPEI ($\hat{\beta}_{dist30}$ = 0.021, CI = [0.01, 0.032]; $\hat{\beta}_{dist20}$ = 0.015, CI = [0.004, 0.026]; $\hat{\beta}_{sink2}$ = -0.023, CI = [-0.035, -0.012]; $\hat{\beta}_{sink3}$ = -0.037, CI = [-0.049, -0.025]; $\hat{\beta}_{temp}$ = -0.015, CI = [-0.027, -0.004]; $\hat{\beta}_{seasonal}$ = -0.016, CI = [-0.027, -0.004]). Profit from cultivated portions of sink3 had confidence intervals overlap the total-cost profit breakeven line at high early SPEI values, while all other landforms maintained a positive profit under the highest early SPEI values. Profit estimates from cultivated portions of temporary ($573/ha CI = [$531, $614]) and seasonal wetlands ($499/ha CI = [$458, $541]) were lower than upland areas ($637/ha CI = [$597, $678]) at average early SPEI. At average early SPEI, profit from cultivated portions of temporary wetlands were $64/ha (10%) less than upland profits and $255/ha above the total-cost profit breakeven line. Profit from cultivated portions of seasonal wetlands was $138/ha (22%) less than upland soybean profit at average SPEI.

As USCV increased (i.e., became more consistently flat), profit from the cultivated portions of dist30 ($\hat{\beta}_{dist30}$ = 0.146, CI = [0.02, 0.272]) increased while sink3 ($\hat{\beta}_{sink3}$ = -0.157, CI =

[-0.289, -0.025]) decreased (Figure 4.17, Appendix C (Table C.8)). Profits from the cultivated portions of uplands, dist20, dist10, sink1, sink2, temporary wetlands, and seasonal wetlands remained unaffected by variation in USCV ($\hat{\beta}_{upland}$ = 0.124, CI = [-0.00, 0.249]; $\hat{\beta}_{dist20}$ = 0.103, CI = [-0.023, 0.229]; $\hat{\beta}_{dist10}$ = 0.115, CI = [-0.009, 0.24]; $\hat{\beta}_{sink1}$ = 0.034, CI = [-0.09, 0.159]; $\hat{\beta}_{sink2}$ = -0.088, CI = [-0.213, 0.038]; $\hat{\beta}_{temp}$ = 0.11, CI = [-0.019, 0.238]; $\hat{\beta}_{seasonal}$ = 0.093, CI = [-0.05, 0.235]).

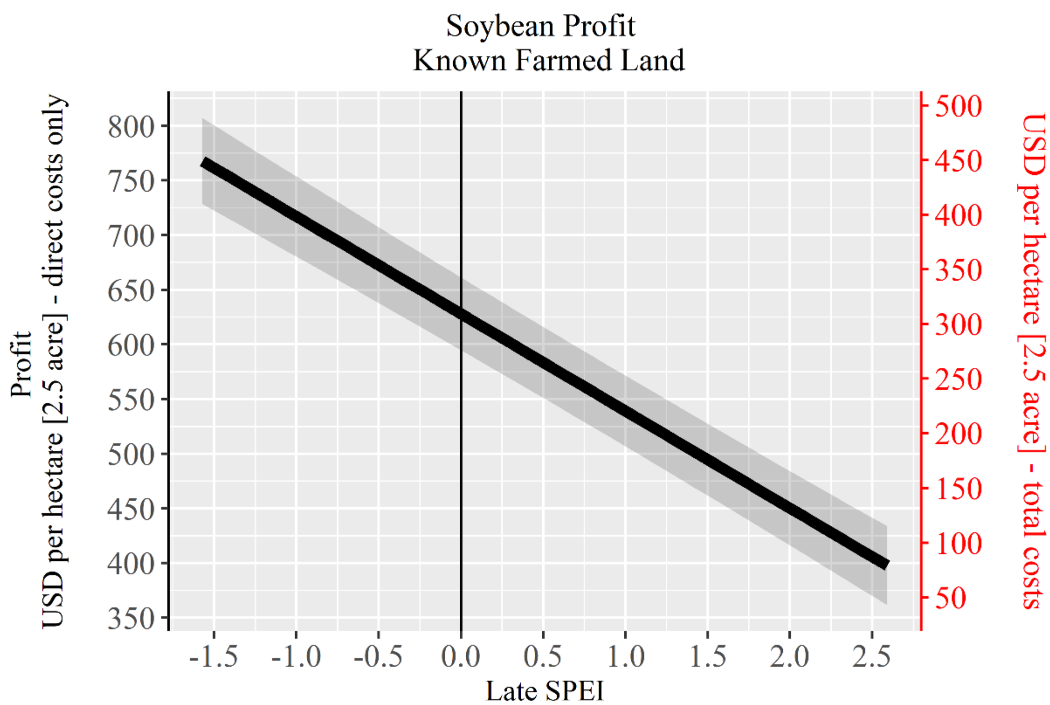

Figure 4.15. Soybean profit estimates with 85% confidence limits in relation to late SPEI from the known farmed land scenario. Estimates were averaged over all landforms while other variables were held at their average. The left y-axis depicts profit in USD per hectare (2.5 acre) when profit is calculated with only direct costs. The right y-axis depicts profit in USD per acre(0.4 ha) when profit is adjusted for total cost (i.e., includes direct and indirect costs). The vertical line depicts the long-term average SPEI.

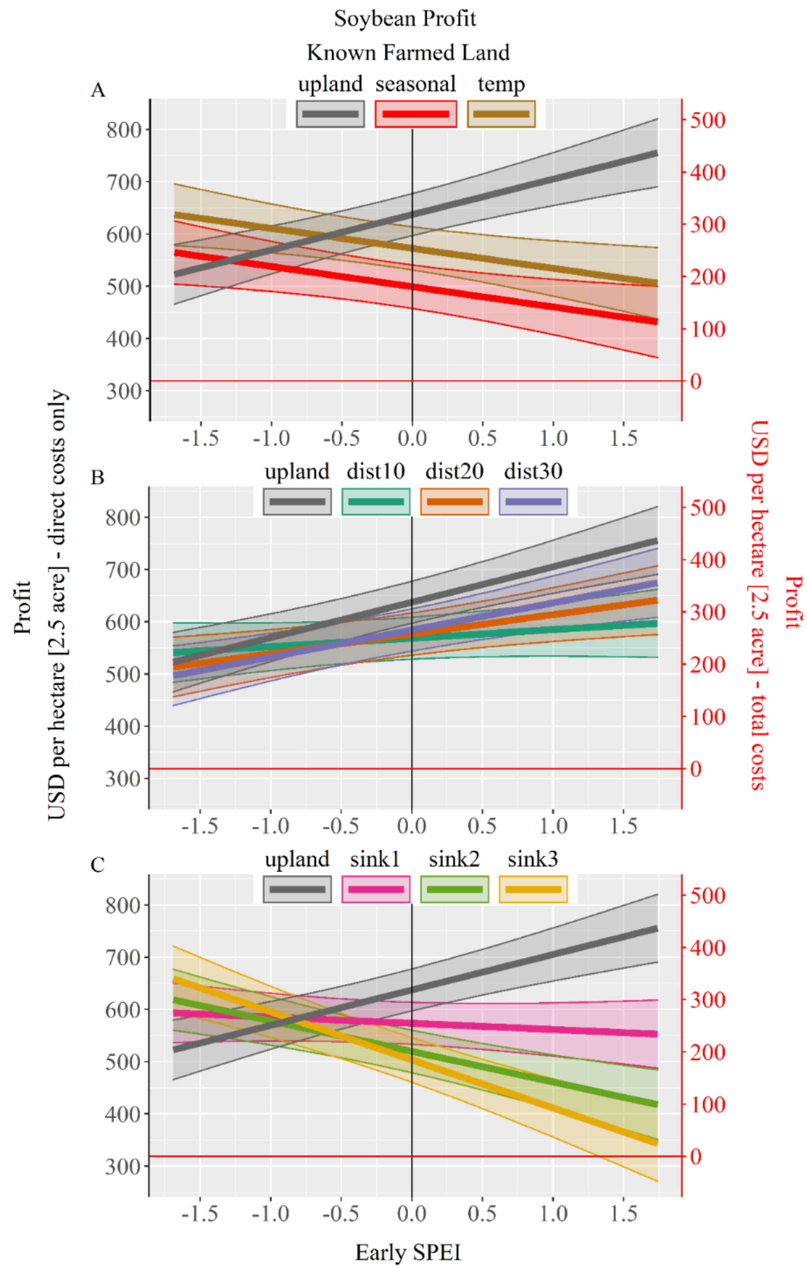

Figure 4.16. Soybean profit estimates with 85% confidence limits in relation to early SPEI for the nine landform categories from the known farmed land scenario. The left y-axis depicts profit in USD per hectare (2.5 acre) when profit is calculated with only direct costs. The right y-axis depicts profit in USD per acre (0.4 ha) when profit is adjusted for total cost (i.e., includes direct and indirect costs). The horizontal red line depicts the '0' profit or breakeven line when total costs are included in profit calculations. The vertical line depicts the long-term average SPEI. A – Corn profit estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn profit estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn profit estimates for landform classes upland, sink1, sink2, and sink3.

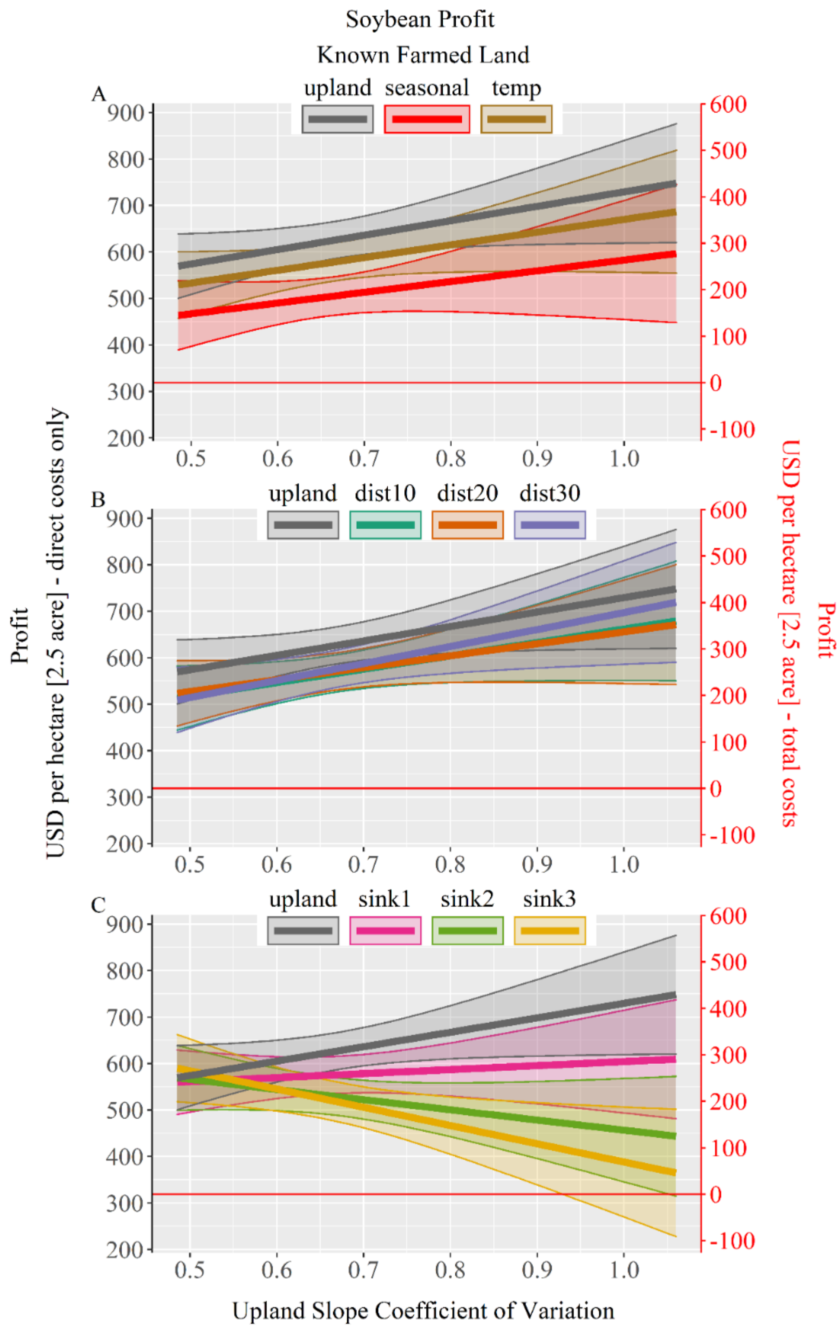

Figure 4.17. Soybean profit estimates with 85% confidence limits in relation to early USCV for the nine landform categories from the known farmed land scenario. The left y-axis depicts profit in USD per hectare (2.5 acre) when profit is calculated with only direct costs. The right y-axis depicts profit in USD per acre (0.4 ha) when profit is adjusted for total cost (i.e., includes direct and indirect costs). The horizontal red line depicts the '0' profit or breakeven line when total costs are included in profit calculations. A – Corn profit estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn profit estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn profit estimates for landform classes upland, sink1, sink2, and sink3.

Soybean Profit — All Farmable Land Scenario

The final model used to explain soybean profit under the all farmable land scenario contained predictor variables including landform, late SPEI, early SPEI, winter SPEI, and an interaction of landform with early SPEI and with winter SPEI (Appendix C (Tables C.1 and C.2)). Increased late SPEI decreased overall soybean profit and resulted in estimated soybean profit lower confidence limits that overlapped the total-cost breakeven line at high values of late SPEI ($\hat{\beta}_{lateSPEI}$ = -0.018, CI = [-0.021, -0.015]; Figure 4.18, Appendix C (Table C.9)).

As early SPEI increased, overall soybean profit for uplands, dist30, and dist20 increased while profit from dist10 remained unaffected by early SPEI variation ($\hat{\beta}_{upland}$ = 0.027, CI = [0.018, 0.036]; $\hat{\beta}_{dist30}$ = 0.019, CI = [0.009, 0.028]; $\hat{\beta}_{dist20}$ = 0.01, CI = [0.001, 0.019]; $\hat{\beta}_{dist10}$ = -0.003, CI = [-0.012, 0.006]; Figure 4.19, Appendix C (Table C.9)). Overall profit from sink1, sink2, sink3, temporary wetlands, and seasonal wetlands decreased as early SPEI increased ($\hat{\beta}_{sink1}$ = -0.012, CI = [-0.021, -0.002]; $\hat{\beta}_{sink2}$ = -0.019, CI = [-0.029, -0.01]; $\hat{\beta}_{sink3}$ = -0.015, CI = [-0.025, -0.005]; $\hat{\beta}_{temp}$ = -0.029, CI = [-0.039, -0.019]; $\hat{\beta}_{seasonal}$ = -0.012, CI = [-0.022, -0.003]). Overall soybean profit from temporary wetlands ($357/ha CI = [$317, $398]) was $237/ha (40%) less than upland profit ($591/ha CI = [$552, $631]) at average early SPEI and dropped below the total-cost breakeven line at ≥0.53 average early SPEI. Overall soybean profit from seasonal wetlands ($245/ha CI = [$205, $285]) was $346/ha (59%) less than upland profit at average early SPEI and was below the total-cost breakeven line across the range of early SPEI.

As winter SPEI increased, overall profit from dist10, sink1, sink2, sink3, temporary wetlands, and seasonal wetlands decreased ($\hat{\beta}_{dist10}$ = -0.01, CI = [-0.018, -0.003]; $\hat{\beta}_{sink1}$ = -0.017, CI = [-0.025, -0.01]; $\hat{\beta}_{sink2}$ = -0.03, CI = [-0.037, -0.022]; $\hat{\beta}_{sink3}$ = -0.029, CI = [-0.037, -0.021]; $\hat{\beta}_{temp}$ = -0.018, CI = [-0.026, -0.011]; $\hat{\beta}_{seasonal}$ = -0.012, CI = [-0.02, -0.004]; Figure 4.20,

Appendix C (Table C.9)). Overall profit from upland, dist30, and dist20 were invariant to variation in winter SPEI ($\hat{\beta}_{upland}$ = 0.001, CI = [-0.007, 0.008]; $\hat{\beta}_{dist30}$ = -0.005, CI = [-0.013, 0.002]; $\hat{\beta}_{dist20}$ = -0.008, CI = [-0.016, 0.000]). Overall profit estimates from temporary wetlands ($399/ha CI = [$357, $441]) were about $180/ha (31%) less than the uplands areas ($579/ha CI = [$538, $621]) at average winter SPEI and fell below the total-cost breakeven line at high winter SPEI values ≥ 1.75. Overall soybean profit estimates from seasonal wetlands ($270/ha CI = [$227, $312]) were $309/ha (53%) less than upland areas at average winter SPEI and were below the total-cost breakeven line across the range of winter SPEI. Overall soybean profit from sink3 and sink2 fell below the total-cost profit breakeven line at ≥ 1.0 and ≥ 0.12 values of winter SPEI, respectively.

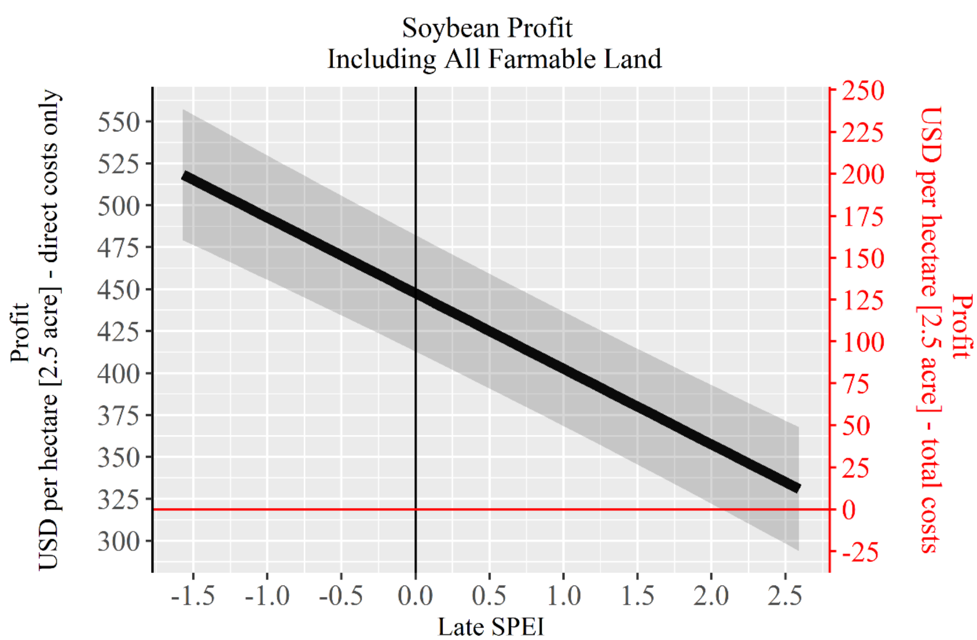

Figure 4.18. Soybean profit estimates with 85% confidence limits in relation to late SPEI from the all farmable land scenario. Estimates were averaged over all landforms while other variables were held at their average. The left y-axis depicts profit in USD per hectare (2.5 acre) when profit is calculated with only direct costs. The right y-axis depicts profit in USD per hectare (2.5 acre) when profit is adjusted for total cost (i.e., includes direct and indirect costs). The horizontal red line depicts the ‘0’ profit or breakeven line when total costs are included in profit calculations. The vertical line depicts the long-term average SPEI.

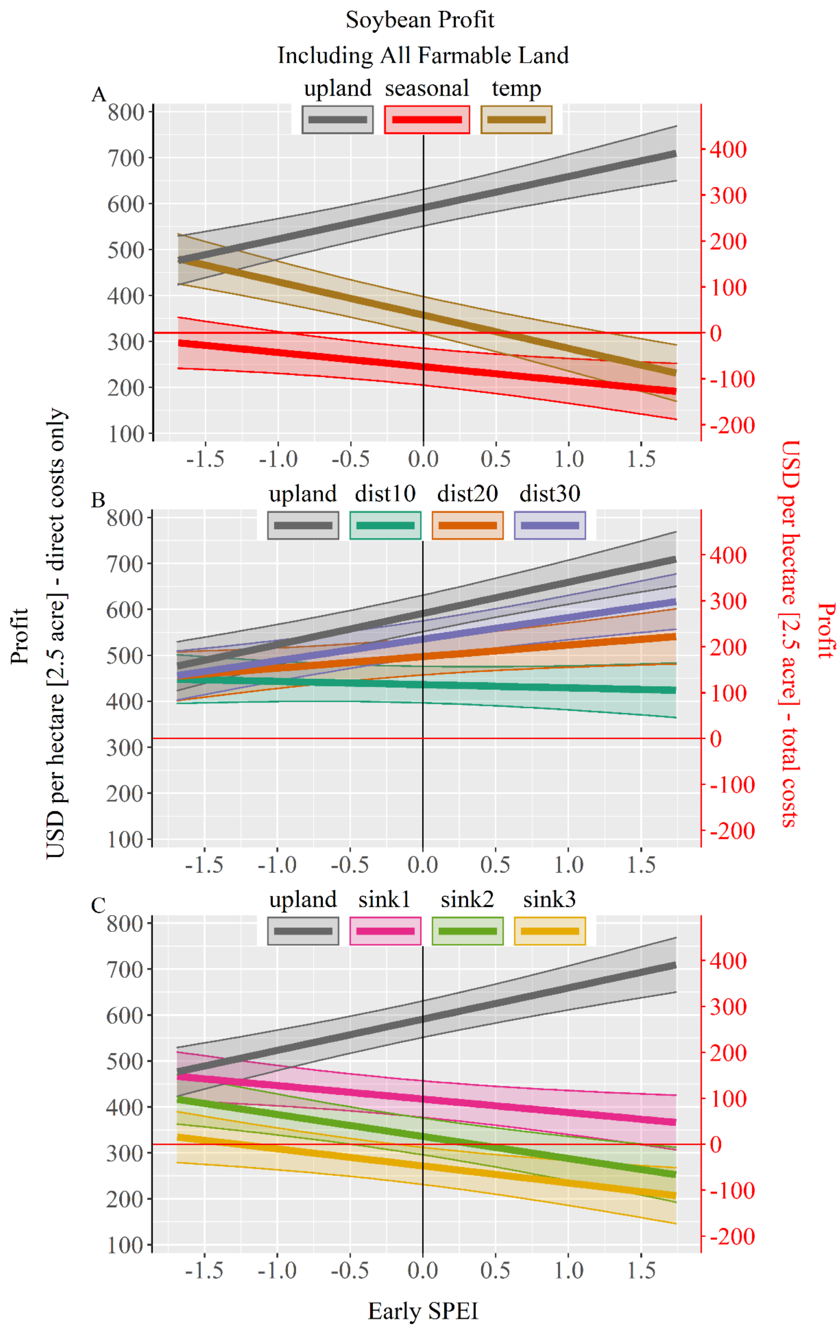

Figure 4.19. Soybean profit estimates with 85% confidence limits in relation to early SPEI from the all farmable land scenario. The left y-axis depicts profit in USD per hectare (2.5 acre) when profit is calculated with only direct costs. The right y-axis depicts profit in USD per hectare (2.5 acre) when profit is adjusted for total cost (i.e., includes direct and indirect costs). The horizontal red line depicts the '0' profit or breakeven line when total costs are included in profit calculations. The vertical line depicts the long-term average SPEI. A – Corn profit estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn profit estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn profit estimates for landform classes upland, sink1, sink2, and sink3.

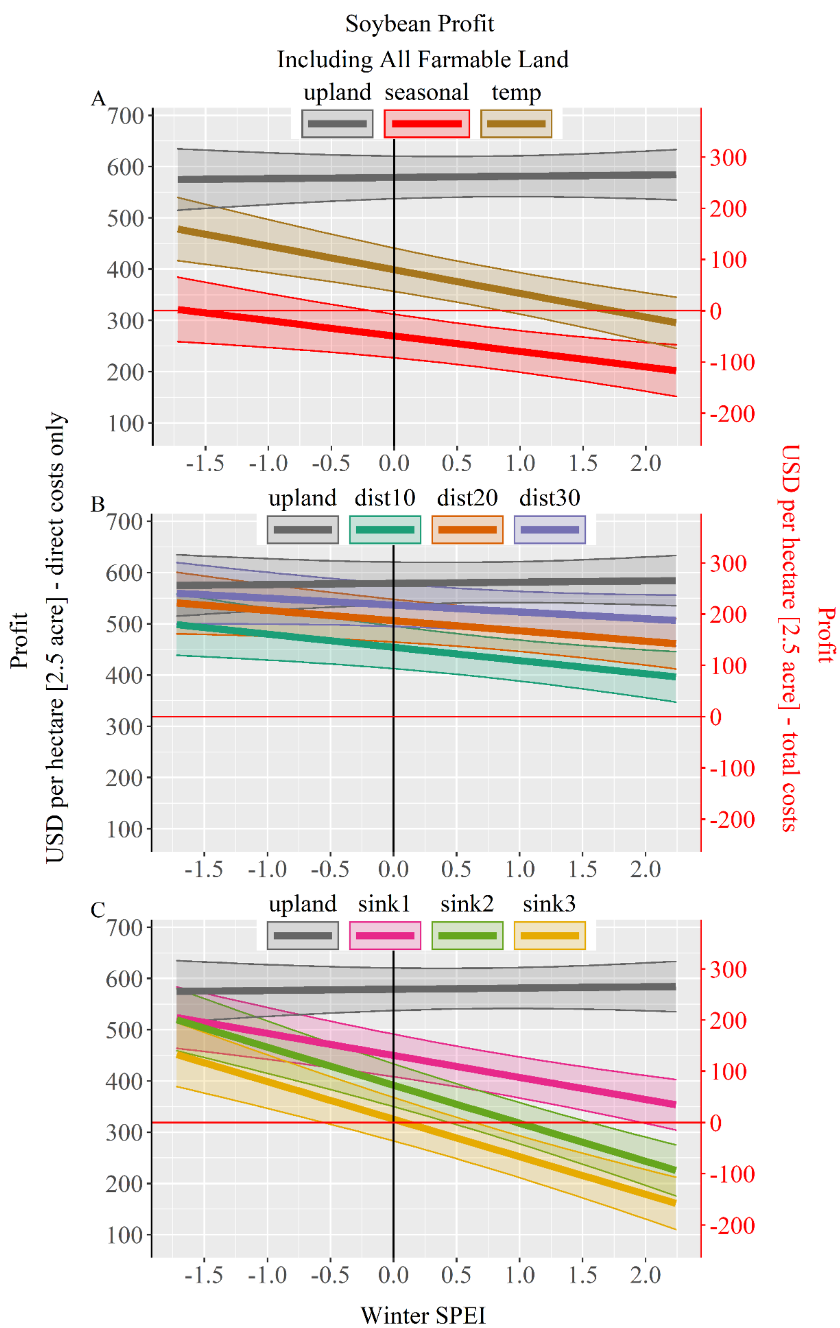

Figure 4.20. Soybean profit estimates with 85% confidence limits in relation to winter SPEI from the all farmable land scenario. The left y-axis depicts profit in USD per hectare (2.5 acre) when profit is calculated with only direct costs. The right y-axis depicts profit in USD per hectare (2.5 acre) when profit is adjusted for total cost (i.e., includes direct and indirect costs). The horizontal red line depicts the '0' profit or breakeven line when total costs are included in profit calculations. The vertical line depicts the long-term average SPEI. A – Corn profit estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn profit estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn profit estimates for landform classes upland, sink1, sink2, and sink3.

Soybean Yield — Known Farmed Land Scenario

The final model used to explain soybean yield under the known farmed land scenario contained predictor variables including landform, late SPEI, early SPEI, winter SPEI, USCV and interactions with landform for early SPEI and USCV predictor variables (Appendix C (Tables C.1 and C.2)). Soybean yield decreased as late SPEI increased ($\hat{\beta}_{lateSPEI}$ = -1.121, CI = [-1.407, -0.836]; Figure 4.21, Appendix C (Table C.10)).

As early SPEI increased, soybean yield increased for uplands ($\hat{\beta}_{upland}$ = 0.839, CI = [0.027, 1.651]) while dist30, dist20, and dist10 remained unaffected by variation in early SPEI ($\hat{\beta}_{dist30}$ = 0.326, CI = [-0.494, 1.146]; $\hat{\beta}_{dist20}$ = -0.027, CI = [-0.847, 0.793]; $\hat{\beta}_{dist10}$ = -0.649, CI = [-1.461, 0.164]; Figure 4.22, Appendix C (Table C.10)). Soybean yield for the cultivated portions of sink1, sink2, sink3, temporary wetlands, and seasonal wetlands decreased as early SPEI increased ($\hat{\beta}_{sink1}$ = -1.631, CI = [-2.445, -0.817]; $\hat{\beta}_{sink2}$ = -1.714, CI = [-2.56, -0.868]; $\hat{\beta}_{sink3}$ = -1.755, CI = [-2.684, -0.826]; $\hat{\beta}_{temp}$ = -1.836, CI = [-2.684, -0.987]; $\hat{\beta}_{seasonal}$ = -0.894, CI = [-1.754, -0.033]). Soybean yield estimates for cultivated portions of temporary wetlands (2.6 Mg/ha CI = [2.5, 2.6]) were similar to that of uplands (2.6 Mg/ha CI = [2.5, 2.7]) at average early SPEI. Soybean yield estimates for cultivated portions of seasonal wetlands (2.4 Mg/ha CI = [2.3, 2.5]) were 0.2 Mg/ha (8%) less than upland areas (2.6 Mg/ha CI = [2.5, 2.7]) at average early SPEI.

Soybean yields for cultivated portions of all groups, except sink2 ($\hat{\beta}_{sink2}$ = -13.898, CI = [-23.068, -4.728]) and sink3 ($\hat{\beta}_{sink3}$ = -15.123, CI = [-25.052, -5.195]) landforms, were unaffected by variation in USCV ($\hat{\beta}_{upland}$ = 2.759, CI = [-6.297, 11.816]; $\hat{\beta}_{dist30}$ = 6.681, CI = [-2.557, 15.918]; $\hat{\beta}_{dist20}$ = 4.675, CI = [-4.562, 13.913]; $\hat{\beta}_{dist10}$ = 7.073, CI = [-2.093, 16.239]; $\hat{\beta}_{sink1}$ = -1.276, CI = [-10.344, 7.792]; $\hat{\beta}_{temp}$ = 1.568, CI = [-7.859, 10.994]; $\hat{\beta}_{seasonal}$ = 4.623, CI =

[-5.752, 14.999]; Figure 4.24, Appendix C (Table C.10)). Cultivated portions of sink2 and sink3 were similar to each other and decreased as USCV increased (i.e., flatter terrain).

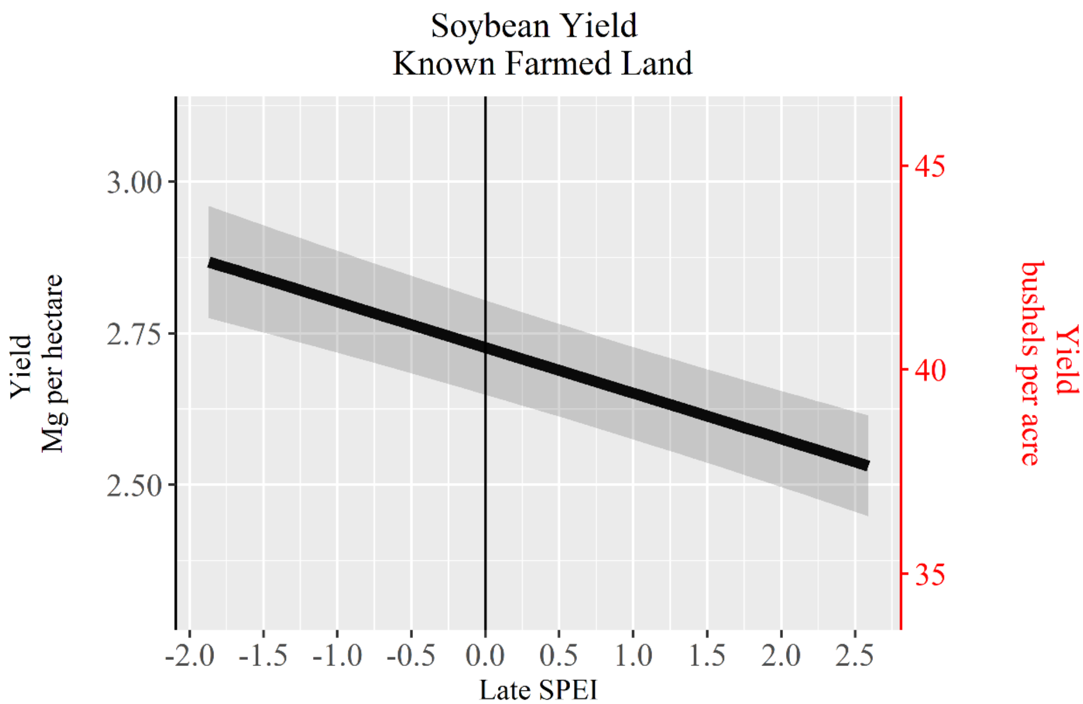

Figure 4.21. Soybean yield estimates with 85% confidence limits in relation to late SPEI for the known farmed land scenario. Estimates were averaged over all landforms while other variables were held at their average. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. The vertical line depicts the long-term average SPEI.

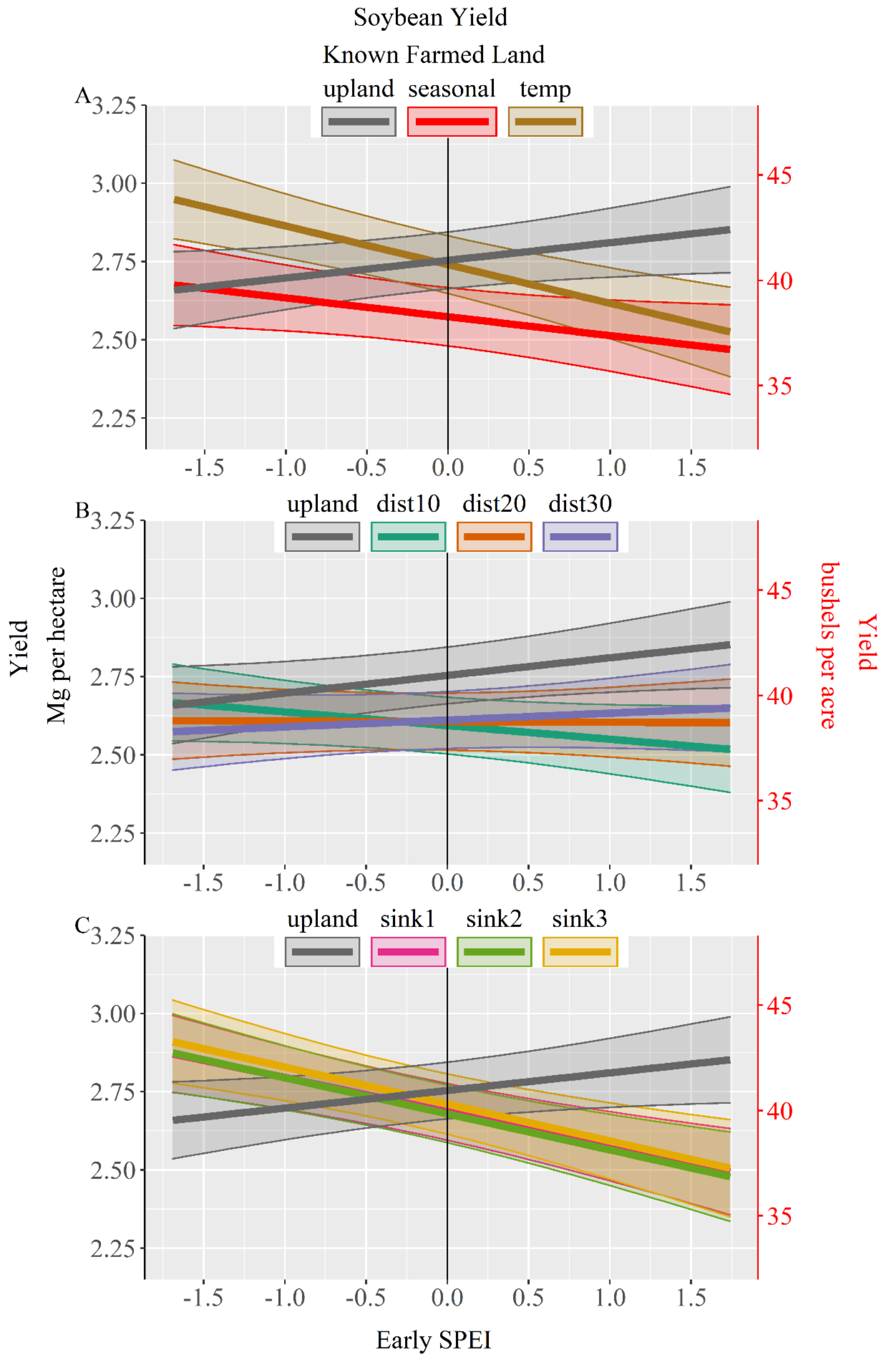

Figure 4.22. Soybean yield estimates with 85% confidence limits in relation to early SPEI for the nine landform categories from the known farmed land scenario. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. The vertical line depicts the long-term average SPEI. A – Corn yield estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn yield estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn yield estimates for landform classes upland, sink1, sink2, and sink3.

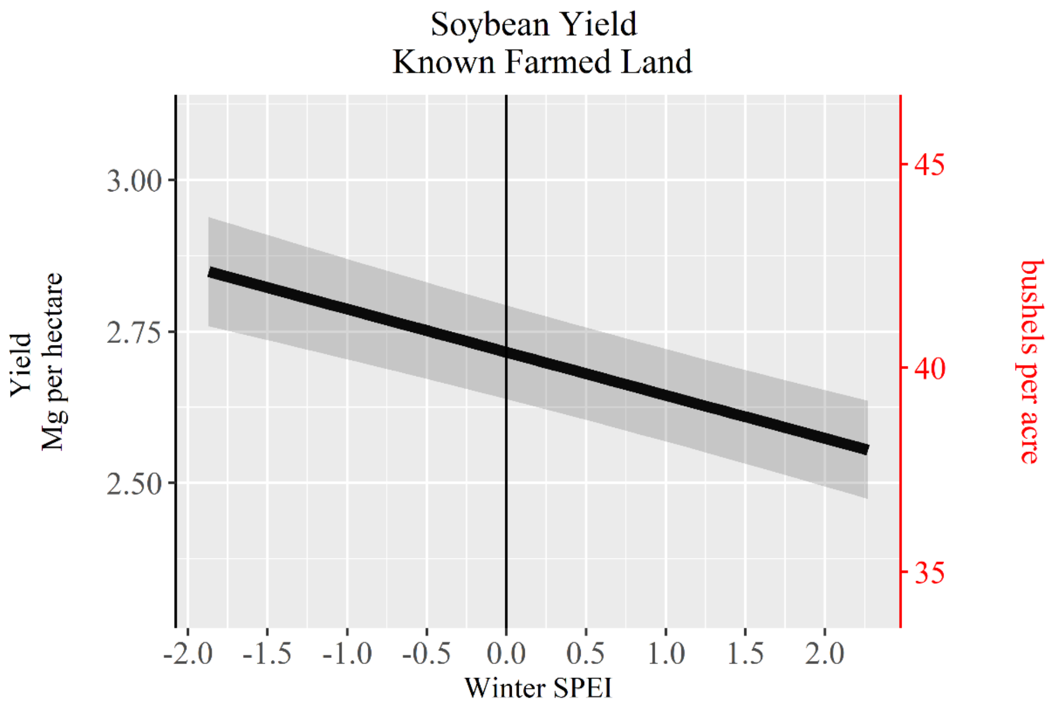

Figure 4.23. Soybean yield estimates with 85% confidence limits in relation to winter SPEI for the known farmed land scenario. Estimates were averaged over all landforms while other variables were held at their average. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. The vertical line depicts the long-term average SPEI.

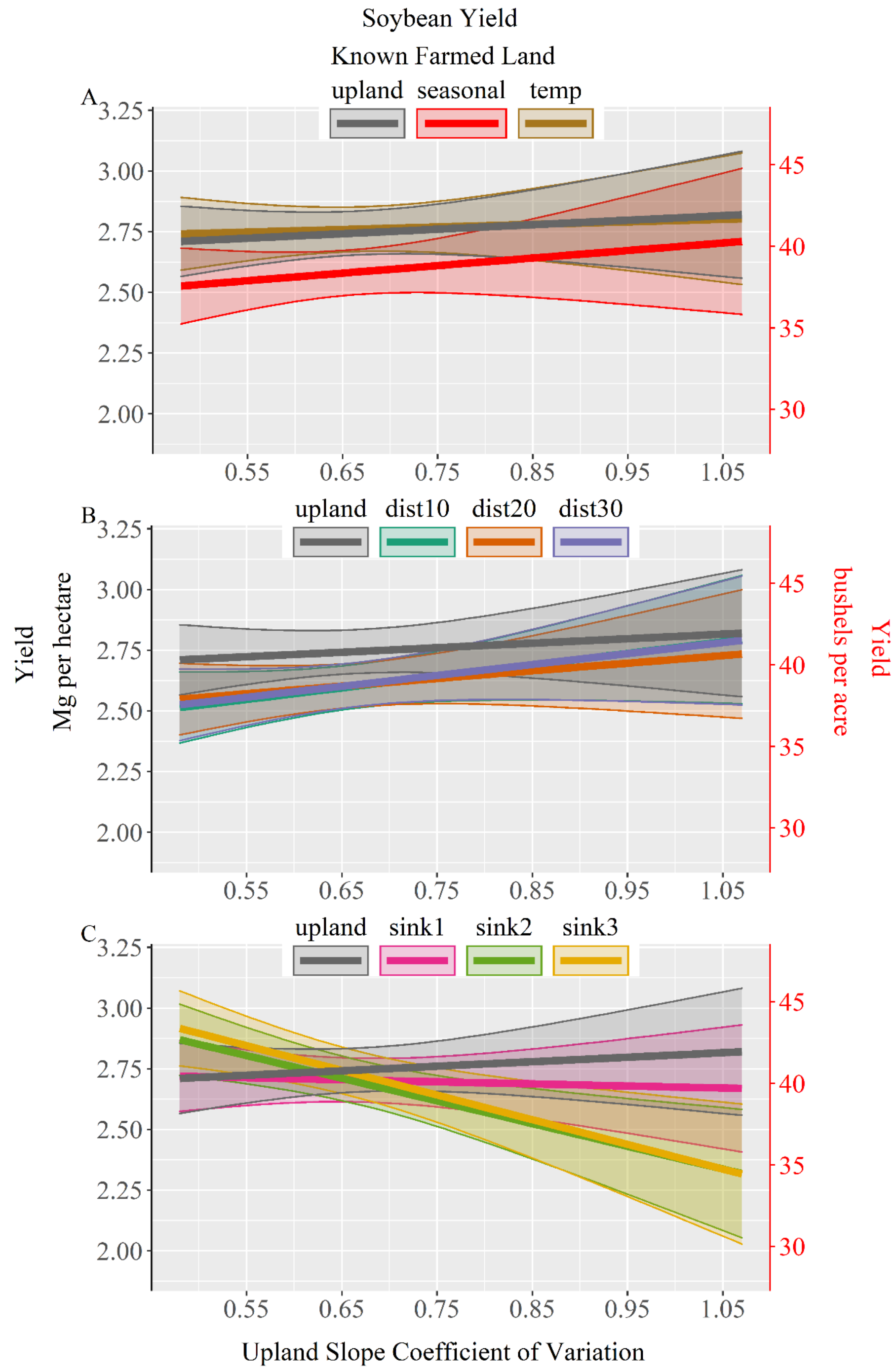

Figure 4.24. Soybean yield estimates with 85% confidence limits in relation to Upland Slope Coefficient of Variation (USCV) for the nine landform categories from the known farmed land scenario. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. A – Corn yield estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn yield estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn yield estimates for landform classes upland, sink1, sink2, and sink3.

Soybean Yield — All Farmable Land Scenario

The final model used to explain soybean yield under the all farmable land scenario contained predictor variables including landform, late SPEI, early SPEI, winter SPEI, USCV and interactions with landform for early SPEI, winter SPEI, and USCV predictor variables (Appendix C (Tables C.1 and C.2)).

As early SPEI increased, overall soybean yield for uplands ($\hat{\beta}_{upland}$ = 1.483, CI = [0.483, 2.483]) increased while yield for dist30 and dist20 were invariant to variation in early SPEI ($\hat{\beta}_{dist30}$ = 0.442, CI = [-0.566, 1.45]; $\hat{\beta}_{dist20}$ = -0.522, CI = [-1.53, 0.486]; Figure 3.25, Appendix C (Table C.11)). Overall soybean yield for dist10, sink1, sink2, sink3, temporary wetlands, and seasonal wetlands decreased with increasing early SPEI ($\hat{\beta}_{dist10}$ = -2.063, CI = [-3.062, -1.065]; $\hat{\beta}_{sink1}$ = -3.425, CI = [-4.424, -2.426]; $\hat{\beta}_{sink2}$ = -4.727, CI = [-5.738, -3.716]; $\hat{\beta}_{sink3}$ = -3.756, CI = [-4.817, -2.695]; $\hat{\beta}_{temp}$ = -5.54, CI = [-6.575, -4.506]; $\hat{\beta}_{seasonal}$ = -3.065, CI = [-4.112, -2.018]). Overall yield estimates for temporary wetlands (1.4 Mg/ha CI = [1.3, 1.6]) were 0.9 Mg/ha (39%) less than upland yield estimates (2.3 Mg/ha CI = [2.2, 2.5]) at average early SPEI. Overall yield estimates from seasonal wetlands (1 Mg/ha CI = [0.9, 1.1]) were 1.3 Mg/ha (57%) less than upland yield estimates at average early SPEI.

As winter SPEI increased, overall yield for upland areas ($\hat{\beta}_{upland}$ = -0.105, CI = [-0.963, 0.753]) remained unaffected while all other landforms decreased ($\hat{\beta}_{dist30}$ = -1.022, CI = [-1.883, -0.161]; $\hat{\beta}_{dist20}$ = -1.349, CI = [-2.21, -0.488]; $\hat{\beta}_{dist10}$ = -1.726, CI = [-2.582, -0.869]; $\hat{\beta}_{sink1}$ = -2.578, CI = [-3.437, -1.72]; $\hat{\beta}_{sink2}$ = -4.878, CI = [-5.751, -4.006]; $\hat{\beta}_{sink3}$ = -4.94, CI = [-5.865, -4.015]; $\hat{\beta}_{temp}$ = -3.309, CI = [-4.197, -2.421]; $\hat{\beta}_{seasonal}$ = -2.077, CI = [-2.988, -1.165]; Figure 4.26, Appendix C (Table C.11)). Overall yield estimates for temporary wetlands (1.6 Mg/ha CI = [1.5, 1.7]) were 0.7 Mg/ha (30%) less than upland yield estimates (2.3 Mg/ha CI = [2.2, 2.4]) at average winter SPEI. Overall seasonal yield estimates (1.1 Mg/ha CI = [1, 1.2]) were 1.2 Mg/ha (52%) less than upland estimates at average winter SPEI.

As USCV increased, overall yield for all landforms increased except sink3 ($\hat{\beta}_{sink3}$ = -5.305, CI = [-16.707, 6.098]) and sink2 ($\hat{\beta}_{sink2}$ = 9.365, CI = [-1.801, 20.532]) which were unaffected by variation in USCV ($\hat{\beta}_{upland}$ = 12.907, CI = [1.807, 24.007]; $\hat{\beta}_{dist30}$ = 15.496, CI = [4.219, 26.773]; $\hat{\beta}_{dist20}$ = 14.172, CI = [2.896, 25.449]; $\hat{\beta}_{dist10}$ = 18.177, CI = [6.984, 29.371]; $\hat{\beta}_{sink1}$ = 14.984, CI = [3.884, 26.084]; $\hat{\beta}_{temp}$ = 31.842, CI = [20.362, 43.322]; $\hat{\beta}_{seasonal}$ = 23.16, CI = [11.37, 34.95]; Figure 4.27).

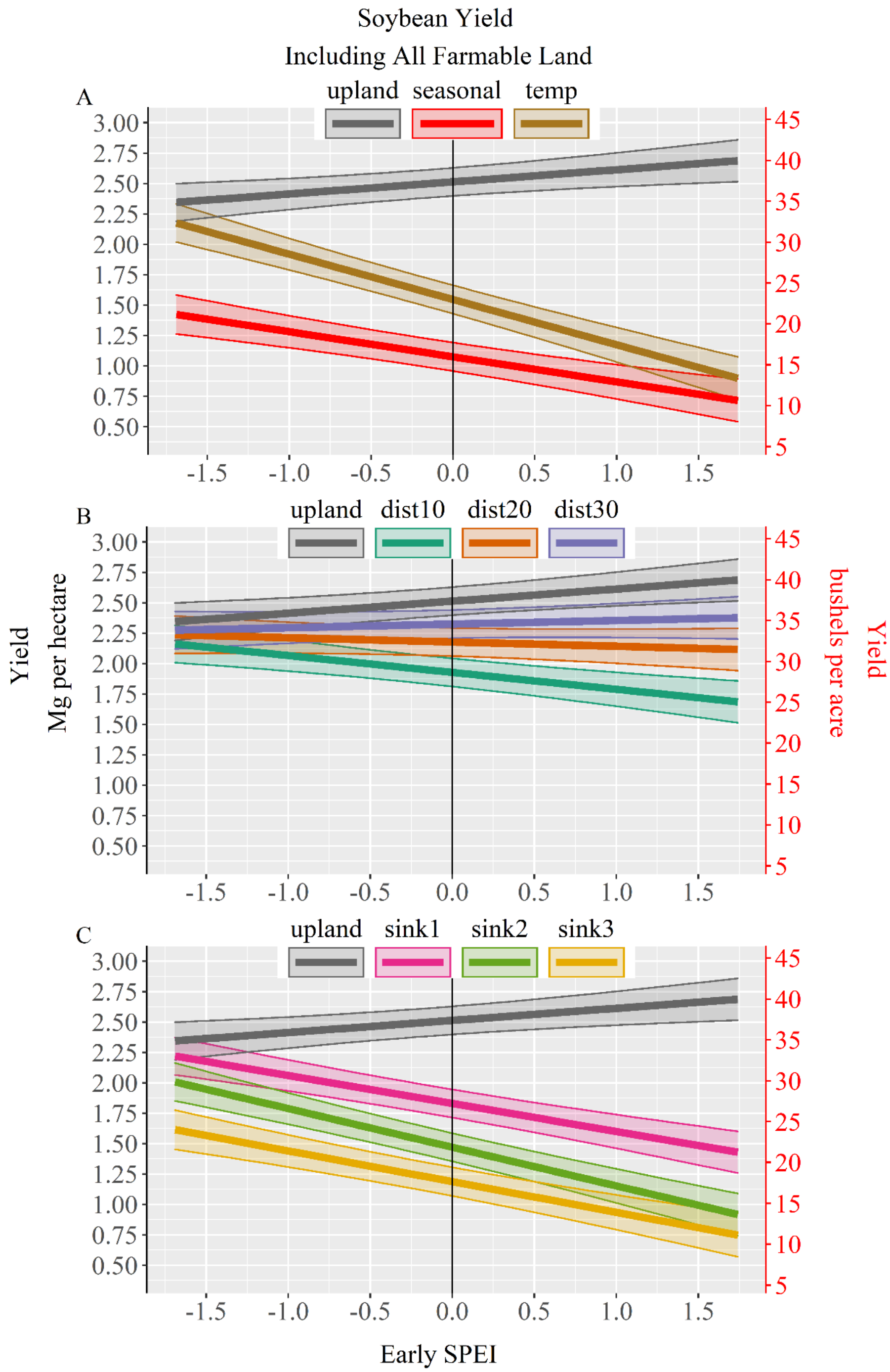

Figure 4.25. Soybean yield estimates with 85% confidence limits in relation to early SPEI for the nine landform categories from the all farmable land scenario. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. The vertical line depicts the long-term average SPEI. A – Corn yield estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn yield estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn yield estimates for landform classes upland, sink1, sink2, and sink3.

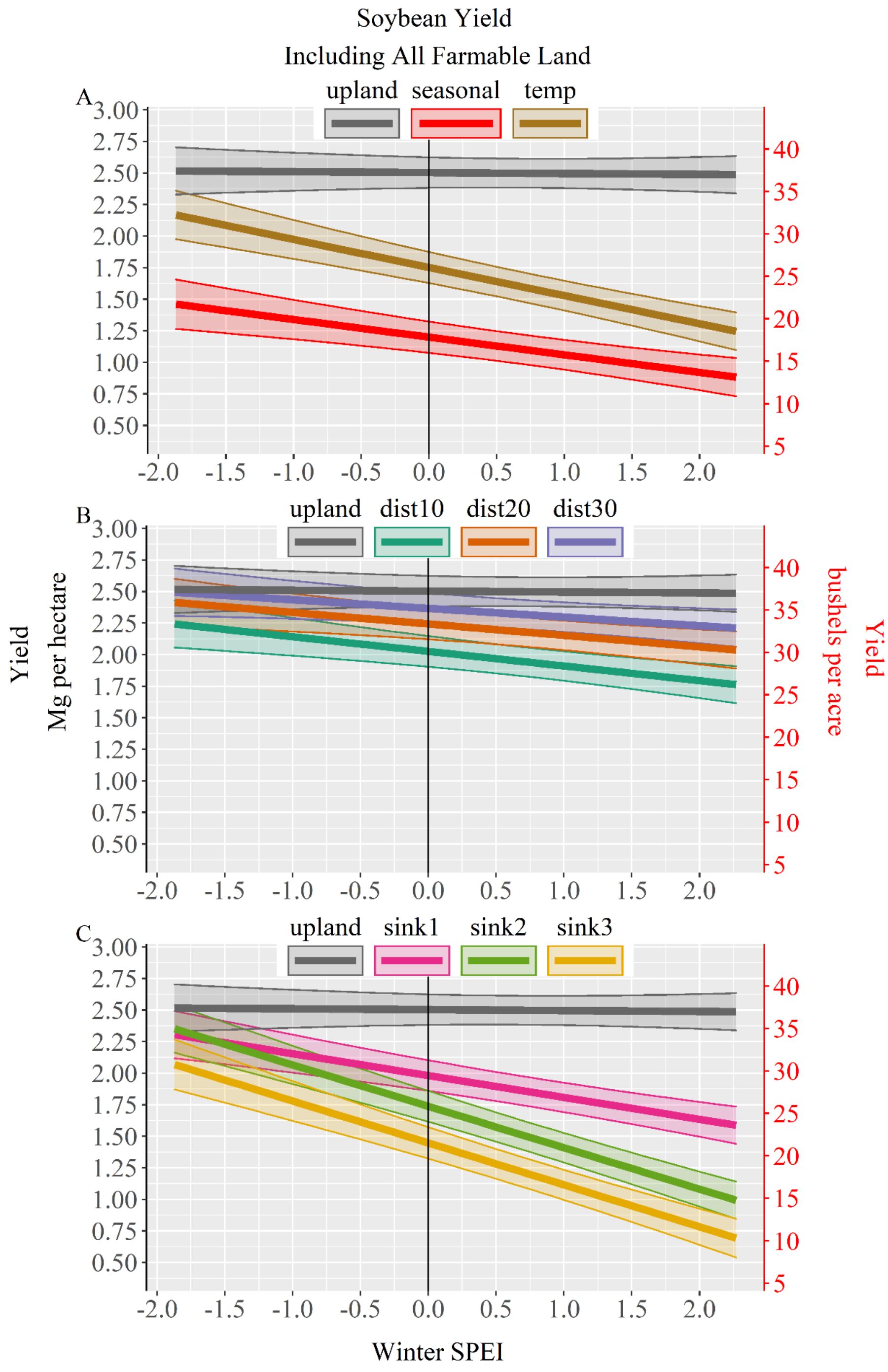

Figure 4.26. Soybean yield estimates with 85% confidence limits in relation to winter SPEI for the nine landform categories from the all farmable land scenario. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. The vertical line depicts the long-term average SPEI. A – Corn yield estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn yield estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn yield estimates for landform classes upland, sink1, sink2, and sink3.

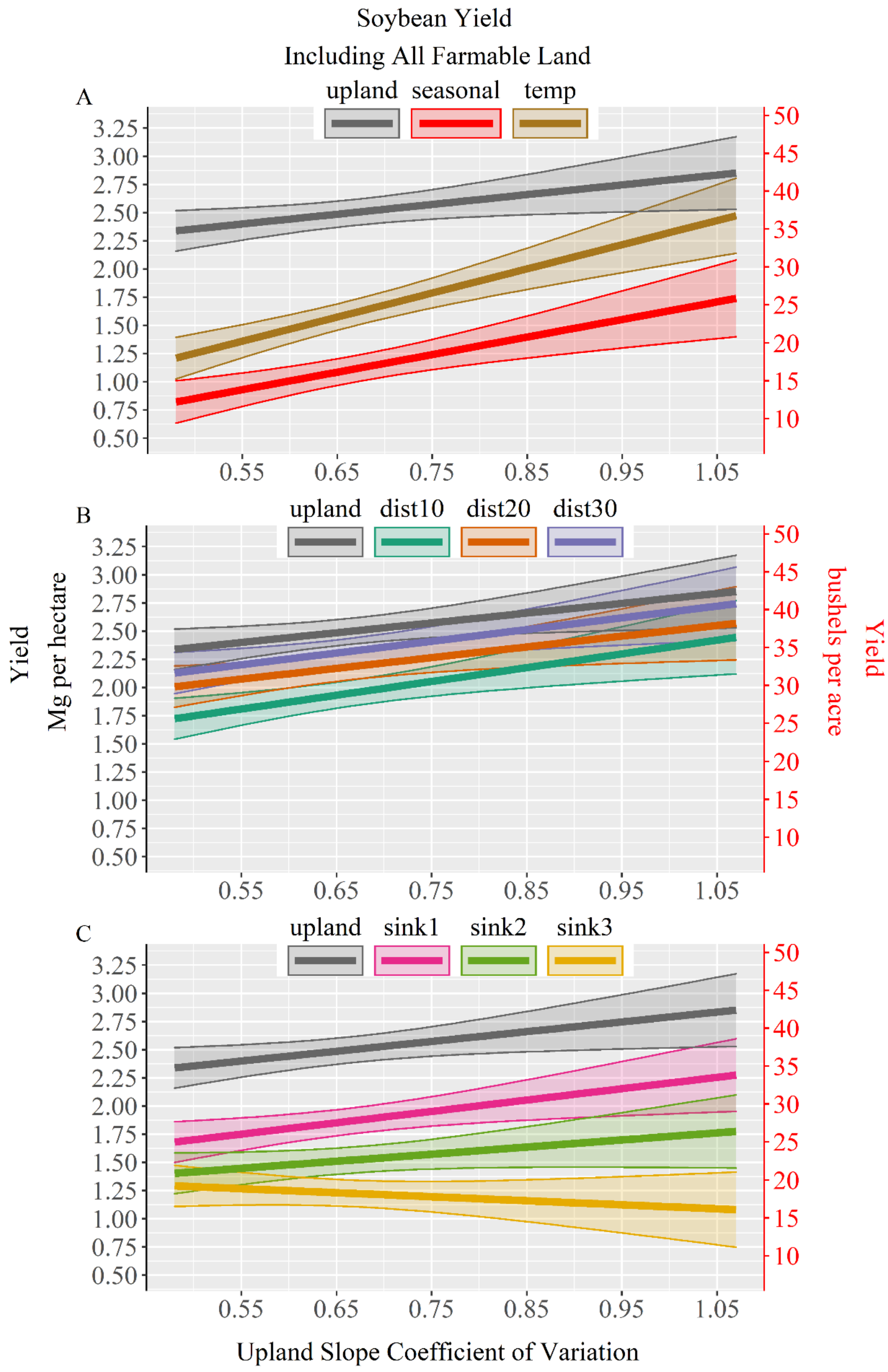

Figure 4.27. Soybean yield estimates with 85% confidence limits in relation to Upland Slope Coefficient of Variation (USCV) for the nine landform categories from the all farmable land scenario. The left y-axis depicts yield in megagrams per hectare. The right y-axis depicts yield in bushels per acre. A – Corn yield estimates for landform classes upland, temporary wetland, and seasonal wetland. B – Corn yield estimates for landform classes upland, dist10 buffer, dist20 buffer, and dist30 buffer. C – Corn yield estimates for landform classes upland, sink1, sink2, and sink3.

Averaged Estimates for Corn and Soybean

Under the known farmed land scenario for average early SPEI, the profit averaged across crop type in cultivated portions of temporary wetlands was approximately \$156/ha (21%) less than upland areas and \$235/ha above a total-cost profit breakeven benchmark. Under the all farmable land scenario for an average early SPEI, the average profit for corn and soybeans in temporary wetlands was approximately \$322/ha (48%) less than upland areas and \$25/ha above a total-cost profit breakeven benchmark. For cultivated portions of seasonal wetlands under the known farmed land scenario at average early SPEI, profit averaged across crop type was \$244/ha (34%) less than upland areas and \$147/ha above total-cost breakeven benchmark. Under the all farmable scenario profit averaged across crop type for the overall seasonal wetland was \$432/ha (65%) less than uplands and \$85 below the breakeven benchmark (i.e., an \$85 loss) at average early SPEI.

For average corn and soybean yields related to early SPEI under the known farmed land scenario, yield estimates for cultivated portions of temporary and seasonal wetlands were about 6% and 16% less than upland yield estimates, respectively. Under the all farmable land scenario relating to the average early SPEI, averaged corn and soybean yield estimates were approximately 42% and 62% less than upland yield estimates.

Discussion

Wetlands of the PPR are some of the most vital habitats for migrating waterfowl and shorebirds in North America; however, these resources are mostly privately owned and managed in an agricultural system. Thus, many of these wetlands are viewed by landowners as part of their business and cultivated in an attempt to profit from the resulting crop. While much is known about the natural ecosystem services provided by PPR wetlands better understanding what role they play in farming operations can provide insights to farmers, conservation planners, insurance companies, or policy makers. Economic evaluations of wetlands often use cash rent prices for a general land-use to apply a financial evaluation. My results have estimated realized monetary values and crop yield for cultivated portions of temporary and seasonal wetlands and of the entirety of the temporary and seasonal wetlands with respect to varying weather conditions. My results suggest farmers are profitable enough on average to cover total costs associated with the cultivated portions of temporary and seasonal wetlands but may be closer to total-cost breakeven (i.e., $0 profit) if the entirety of the wetland landform is considered. However, profit and yield were greatly influenced by weather during the previous winter, early growing season, and late growing season.

Profit and yield of corn and of soybeans responded similarly to early growing season conditions. Corn profit and yield for upland areas under either known farmed or all farmable land scenarios was either unaffected or slightly increased from dry (low SPEI) to wet (high SPEI) conditions of the early growing season, but most wetland-related landforms (e.g., sink1, sink2, sink3, temporary and seasonal wetlands) showed decreasing trends in profit and yield from dry to wet early season growing conditions. Soybean profit and yield in uplands increased with increased early wet conditions in contrast to corn, but similar to corn, soybean yield and profit decreased in wetland landforms in response to wetter early season weather.

Although a landform and late growing season interaction was not an important variable, the late growing season factor had strong positive effect on corn yield and a strong negative effect on overall soybean profit and yield from cultivated areas (i.e., known farmed land scenario). The strong positive effect for corn may be related to later stages of growth, which coincide with the late SPEI metric, being the most susceptible to drought and thus were benefiting from wetter conditions during those times (Çakir 2004). The strong negative effect for soybeans is likely because the late SPEI (June–October) time period and its coincidence with the timing of soybeans' most sensitive growth stage to water stress (R4 to mid R5) in North Dakota (Morrison et al. 2006; Kandel and Endres 2019). Water stress during the R4 to R5 stage can reduce seed size and, in turn, reduce yield (Morrison et al. 2006).

Winter precipitation conditions, because it can be calculated prior to the planting season, may be a parameter that farmers could utilize to assess whether to plant in low spots in the spring to increase their profitability and average yield. Profit and yield responded to winter precipitation conditions with generalized and landform-specific effects. Corn profit and soybean yield declined, without respect to landform, in response to increasing winter precipitation in the known farmed land scenario. When winter water conditions were interacted with landform, corn profit and yield responses from uplands were either invariant or negative while most other landforms decreased. Similarly, winter weather conditions did not affect soybean upland yield or profit, whereas wetter winter weather decreased soybean yield and profit in most other landform categories. Farmers may already be accounting for wetter conditions because wetter winter conditions likely result in wetter conditions in wetlands during the start of planting and may limit the ability to plant the entire wetland area. In Chapter 3, I found that over half the temporary wetland area and nearly a third of seasonal wetland area was planted on average. However, I assumed that farmers did not plant through water and only planted where soil moisture allowed, but the results still suggest a negative relationship with winter precipitation for most wetland-related landforms.

I used two spatial variables at the field level to increase control over variation in profit and yield estimates. The spatial variables that fit well could be used by conservation planners to help tailor programs to particular parts of the farming landscape. UPI was only in the overall corn yield and profit models and had a positive association to upland areas >10 m from wetlands. The associations were mixed for the other landforms and may warrant further exploration or comparison to similar parameters to test if the relationship is a good predictor for other crop fields outside of this study. Similarly, USCV was in five of eight models and generally had a positive influence on each metric estimate across its range except for sink2 and sink3. Further study and examination of USCV would also be needed to determine its usefulness in profit and yield estimation and prediction. Yet, these two variables may help conservation planners determine areas to target for conservation efforts or to provide appropriate payment amounts for land enrollment in conservation programs.

Ponded water within wetlands can cause farmers to view wetlands as nuisance areas and hinderances to farming operations. Increased land and potential for profit has likely played a part in farmers wanting to drain wetlands. Although this study does show that farmers are already profitable on cultivated portions of wetland areas and less profitable on the entirety of wetland area, there may need to be caution when interpreting these results as a reason to drain wetlands. A study from Iowa reported from 77 corn and soybean fields, that crops cultivated within wetlands were not profitable in four out of nine years (44%) and less profitable than upland areas in eight of nine years (Fey et al. 2016). Yet, their study was conducted in areas and wetlands that had drain tile previously installed, which were intended to lower water levels and improved the odds of cultivating and harvesting crops from those wetlands. Chapter 3 of this dissertation using similar profit calculations reported frequency of losses for soybeans in temporary wetlands as 20% and in seasonal wetlands as 29% and for corn in temporary wetlands as 35% and in seasonal wetlands as 44% from 19 years of data. Though more examination may be needed, the frequency of loss between these two studies appears similar. This may suggest that even if wetlands are drained, the wetland areas may not produce crops with similar yields to upland areas. Another study reported 56% of drained and consolidated wetland basins in the PPR in Alberta, Canada yielded a financial loss, with one farmer experiencing financial loss in 90% of their drained and consolidated wetlands (Clare et al. 2021). The authors also reported that total and average profits were better than profits in drained and consolidated wetland basins. Therefore, enrolling agricultural wetlands in conservation programs may be a method for farmers reduce input costs and have more consistent profit from wetland areas without draining.

This study could have been improved with more complete sets of data and financial records. Complete precision agriculture data sets are often low priority for farmers. Even with the intent to record these data fully and accurately, there are often complications with machinery and precision hardware and software that can make it difficult to accomplish. Stressing the importance to study participants of accurately recording all inputs may help improve datasets in a prospective study. Also, precise tracking of inputs prices may not occur or providing those financial datasets may not be information that farmers want to provide to researchers. A financial tracking worksheet provided to participating farmers may help streamline the process for a study and for farmers. Additionally, this study likely underrepresents the costs to prepare wetland areas for planting. Direct costs were only attributed to the areas planted and would therefore exclude preparation costs on portions of wetlands that were manipulated (i.e., burned, disked, mowed, etc.) in the fall but were too wet to plant in the spring. The preparation time and "wear and tear" on farming machinery is likely higher in wetland areas compared to the surrounding field (see Chapter 5). Accounting for the preparation costs would involve tracking those manipulations spatially and estimating their costs, which is data this study did not have but is data that could be used to better inform costs related to cultivating wetlands.

This study provides a first step into furthering understanding of how wetlands fit into farming operations. However, this study was conducted with data only from the Drift Prairie in North Dakota. To have a better understanding of wetlands relating to farming operations, a broader spatial extent of data could help in understanding wetlands in other physiographic sections of the Prairie Pothole Region. An effort to expand the extent of data may help to better inform incentives in other areas and have a larger impact on conservation efforts.

Conservation Implications

The effects of cultivation on ecosystems services of wetlands, or even the lowered profits and financial losses from cultivating wetland, may not individually be enough motivation for farmers to investigate or develop alternative management strategies for those areas. However, those effects combined may encourage, or at least help to inform, alternative management strategies for agricultural wetlands which could increase farm profitability and benefit other ecosystems services. Alternative management strategies could involve enrollment into, or development of, conservation programs that include incentive payments or cost-share agreements for alternative AW conservation practices. A management option for AW that could enhance ecosystem services of AW would be ideal from a conservation perspective, however, options that financially benefit farmers will likely be the most supported and utilized by farmers (Saltiel et al. 1994; Cary and Wilkinson 1997; Sweikert and Gigliotti 2019).

Examining crop profit under the all farmable land scenario and including total costs in profit calculations may provide farmers and conservation agencies with a long-term assessment of farmers' operations and how wetlands factor into farm profit. However, examining profit in a more traditional farmer perspective under the known farmed land scenario, may help conservation agencies have a better understanding of farmers' profit expectations from their land. These results provide an estimate of profit that a farmer could reasonably expect, given standard practices, to get from cultivating within the designated landforms in the Drift Prairie of North Dakota. This study may inform conservation compensation levels for farmers in the Drift Prairie that use temporary and seasonal wetlands differently (i.e., enroll in conservation program) than was assumed in this study.

Conservation programs provide payments to farmers for alternative management practices that benefit conservation. The Natural Resources Conservation Service currently has a program entitled Prairie Pothole Water Quality and Wildlife Program (PPWQWP) which incentivizes farmers to not drain cropped wetlands under 2 acres in size. Depending upon one of three potential enrollment levels that a farmer chooses, annual payments range from \$300/ha to \$400/ha (\$121/acre to \$162/acre) for North Dakota land in 2021. These values are below the direct-cost-only profit levels estimated for temporary and seasonal wetlands related to early SPEI under the known farmed land scenario but are above estimates related to average early SPEI from the all farmable land scenario using either direct-cost-only or total-costs profit methods. Other conservation programs such as the Conservation Reserve Enhancement Program and Conservation Reserve Program are land retirement programs that involve enroll larger sections of land than the size of the wetlands in this study. Although, these are viable options to improve ecosystems services on cropland, there will still remain many wetlands in active crop fields. For agricultural wetlands, the PPWQWP is directly comparable to this study. Also, Chapter 2 found that agricultural wetlands may still need some type of disturbance to be more useful to spring migrating shorebirds and waterfowl. The need for some disturbance and revenue generation in wetlands may present an opportunity for planting more water-tolerant annual or perennial plants that could be beneficial to wildlife and potentially hayed for revenue generation by farmers.

Factors other than profit and yield may influence the decision of farmers on management strategies for wetland areas and for farmer acceptance/enrollment into conservation programs (Wachenheim and Lesch 2014; Wachenheim et al. 2018). One important factor involves a human dimension component, such as what farmers expect to yield or profit from wetland area. Farmers may not examine their own data to the extent of this study but will still have expectations for yield and profit that they assume come from the landform's types in this study. Determining those yield and profit expectations is another step to understanding the role of wetlands in farming operations.

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CHAPTER 5. FARMERS' YIELD EXPECTATIONS AND FACTORS AFFECTING DECISIONS TO CULTIVATE WETLANDS WITHIN AGRICULTURAL FIELDS

Abstract

Despite drainage of almost half of the wetlands in North Dakota, many of the remaining wetlands reside in private cropland. Farmers have recently brought more wetland areas into crop production in part because of commodity prices, land values, and government policies. These wetlands can pose a management challenge to landowners and farmers because agricultural wetlands can pond water and increase financial risk due to a killing a planted crop. Financial and other factors likely motivate farmer's management of wetlands in their crop fields. Understanding motivation to incorporate wetland or low spot areas into crop production may help to inform better alternatives and support for farmers managing wetland areas in their fields. I queried farmers with in-person interviews and an online opt-in questionnaire to gain insights into the farmers perceptions of wetlands in their crop fields. The questions related to yield and costs comparisons of wetlands to surrounding land, factors influencing their decision to attempt to farm wetlands, and if they would continue to farm a wetland based on combinations of its size and financial history scenarios. I collected responses from 18 participants. Most respondents (n = 16) reported that they anticipated a yield from a low spot or wetland to be about the same or higher than the yield from the surrounding field. The top three factors influencing decisions to farm a wetland were the ability to get machinery into the wetland, keeping the area eligible for prevented plant insurance, and the frequency of ponded water in the wetland. This study may help tailor conservation efforts and programs to better align with farmers' motivations to farm wetlands and address possible misconceptions held by farmers about wetland areas.

Introduction

Much of the farmable land within North Dakota falls within the Prairie Pothole Region (PPR). The fertile soils, climate, and rolling landscape make the region conducive to farming. Prior to European settlement, wetlands comprised about 11% of the area of North Dakota (Dahl 1990). Almost half of North Dakota's wetlands have been drained, yet most of the remaining small wetlands in parts of the PPR are located within cropland (Dahl 1990; Niemuth et al. 2006). These wetlands pose a management challenge for farmers cultivating crops and may result in farmer increasing overland and subsurface draining or waiting for conditions dry enough to cultivate the area. Understanding the financial value of these areas to crop production (see Chapter 3 and 4) is only part of determining useful management alternatives for agricultural wetlands. It is equally, or maybe even more important, to understand how farmers perceive and integrate wetlands as part of their farming operations.

Wetlands of the PPR are classified by hydroperiod but operate on a hydrological continuum driven by wet-dry climate periods (Euliss et al. 2004). The pattern of wetting and drying, which cycles nutrients in wetland systems, is a main factor in the biological and biophysical processes of these wetlands and has shaped the plant life and wildlife that use the region (Kantrud et al. 1989; Laird et al. 2003; van der Valk 2005). The biological and biophysical processes which have made the region productive for wildlife, have also made the region productive for agriculture. This productivity has led to an increase in cropland which has significantly altered the landscape. The prairie regions of the United States have lost >75% of grasslands and >49% of wetlands (Dahl 1990; Samson and Knopf 1994) primarily because of agricultural expansion. In North Dakota, there has been an increase in the amount of land in agricultural production over the past 50 years because of commodity prices, land values, and government programs and policies (Lark et al. 2015; Brandes et al. 2016). North Dakota was identified as a ‘hotspot’ of new cultivation with most of the cropland expansion located east of the Missouri River within the Prairie Pothole Region (PPR) (Lark et al. 2015). However, this expansion of cropland has resulted in the use of many areas of marginal lands (e.g., less productive). For example, 55,000 hectares of wetlands were cultivated from 2008–2012 in North Dakota, South Dakota, and Minnesota, which had not been cultivated since at least 2001 (Lark et al. 2015). However, the newly cultivated wetland areas were likely still susceptible to water ponding issues for crop production.

Many wetlands in the PPR reside in privately owned cropland (Janke 2016). Therefore, conserving the remaining wetlands requires cooperation and collaboration with private landowners. How landowners view, value, and make decisions on the manipulation of wetlands within their fields is an important factor that influences the vegetation, hydroperiod, quality, and in turn, use of wetlands by wildlife. Yu and Belcher (2011) reported that farmers’ attitudes towards wetlands was an important factor in the conservation decisions on their land. Many farmers believe that decisions of how land is used is the right of the landowner (Wachenheim et al. 2018). Therefore, when small wetlands occupy land that could potentially be farmed and become a source of income, regulations that limit landowners’ ability to farm within wetlands can cause negative attitudes towards conservation programs and regulation.

Many farmer surveys are administered to assess perceptions of ecosystem services provided by natural landscape features (e.g., wetlands, grasslands) or to assess various aspects of conservation programs, such as willingness to enroll, payment rates, qualification requirements, and contract length (Martin 2008; Yu and Belcher 2011; Addo et al. 2017), but none have specifically addressed factors affecting decisions to cultivate wetlands in existing cropland or farmers expectations for yield in those areas. One study examining wetland conversions in the PPR was done under varying scenario-based governmental wetland regulations and policies related to crop insurance subsidies and biofuel requirements that may have influenced motivations at that time (van Kooten and Schmitz 1992). Other studies on land use have cited current net present value of costs and benefits when considering conservation enrollment and land retirement (Featherstone and Goodwin 1993; Claassen and Tegene 1999). Some studies have estimated the wetland value to owners, but estimates varied widely and overall values were based on land value or potential cash rent (Leitch and Hovde 1996; Leitch and Fridgen 1998). Gelso et al. (2008) reported that surveyed farmers were less willing to pay rent for land where wetland area was dispersed into multiple small wetlands than the same land where wetland area was concentrated in a single wetland. The authors associated this perceived drop in value to the "nuisance" of farming around or through each wetland. However, few surveys have inquired about farmers' expectations regarding farming wetlands or what factors play a role in deciding to attempt farming within wetlands.

In this survey, I attempt to understand how respondents perceive low spots (i.e., wetlands) within their fields, what factors influence their decisions to attempt farming these areas, and how these areas compared in cost and yield to the surrounding field areas. Insights from responses may help to inform conservation programs, policy, or improve future survey structure and questions.

Methods

Study Area

Historically, the PPR was a vast grassland interspersed with depressional wetlands. In the Drift Prairie, a physiographic region within the PPR, wetland densities can reach >57/km^2 (Dahl

2014), mainly composed of temporary and seasonal wetlands. Most wetlands are <0.5 ha in area but can reach sizes of >40 ha for permanent bodies of water (Kantrud et al. 1989; Batt 1996; Niemuth et al. 2010). However, 39.3 million acres (~89%) of North Dakota were classified as farm operations (NASS 2017).

The cropping system in this region is typically a rotational planting system. In the Drift Prairie, corn and soybeans are the most common crops planted every other year in each field. However, North Dakota has a wide variety of crops that can be cultivated, including but not limited to spring wheat, durum, malting barley, corn, soybeans, oil sunflower, canola, flax, field peas, oats, lentils, yellow mustard, safflower, buckwheat, millet, large chickpea, winter wheat, rye, and sugar beets.

Survey

The population of interest for this survey was North Dakota farmers within the Drift Prairie. The survey questionnaire (Appendix D) was administered during the early spring of 2020 by in-person interviews and an online opt-in survey method. Interviews conducted targeted Drift Prairie farmers, but the online opt-in method (described below) may have had a wider audience. This survey was designed as a qualitative survey with which the questions presented could encourage additional comments and thoughts to be expressed that could provide informative and insightful responses (Drury et al. 2011) related to farmers' decision processes and views towards wetlands or low spots in their agricultural fields.

It is important to note the background of the interviewer to provide more context to the interviews and acknowledge potential biases which may be inherent to the in-person interviews. I personally conducted all the interviews and have a background in wildlife and ecology research which was made known to the participants prior to the interview. I was also required to get the survey questionnaire approved through North Dakota State Universities Internal Review Board and take trainings pertaining to surveying and interviewing human subjects to ensure the protection of the rights and wellbeing of the participants. No personal identifying information was recorded for any participants, and no incentives were offered or provided for participation in this study.

There were two methods through which the survey questionnaires were delivered. The first method was through in-person semi-structured interview (Drury 2009) with farmers who allowed wetland bird surveys to be conducted on their lands as a part of another study in the Drift Prairie evaluating waterbird use of manipulated wetlands within agricultural fields (Chapter 2). These interviews were conducted with one participant per interview and typically conducted at the participant's residence. For the interview method, I disseminated a paper copy of the questionnaire to the participant while I was available to further explain questions if needed as the participant worked through the questions. After or during the survey, participants often asked questions or made comments which I paraphrased for understanding and recorded. This strategy helped to refine or reword questions in which the wording or understanding was unclear and adjustments to questions were made prior to additional interviews or dissemination of the questionnaire. The time to complete the questionnaire by the respondents during the interviews was not recorded.

After most of the in-person interviews were conducted, then the second method for the survey, the online questionnaire, was disseminated. This questionnaire was an online opt-in sample conducted with a web address link to an electronic form, which was distributed in two consecutive monthly electronic mail newsletters through a grain association based in North

Dakota. The number of recipients was not provided to me. The average time to complete the electronic questionnaire was 13 minutes.

Certain questions in this survey asked about the respondents' family situation, relation to the farm, income relation to the farm, acres farmed, agricultural technology used, and if they had ever enrolled in conservation programs. Other questions were related to their opinions of how low spots compare to the surrounding fields' yield, preparation costs, and frequency of use.

In one question, respondents were asked what factors affected their decisions to attempt to farm a low spot within their crop fields (Appendix D - Question #8). They were asked to rank their top three choices (i.e., 1 being their primary factor effecting their decision) and mark all other listed factors as considered but not in their top three factors or not considered as a factor influencing their decision to attempt to farm low spots. Effectively, this was a scale of 1–5 with 5s equating to no consideration given to the factor. I totaled the numeric scores and subtracted them from highest score possible (i.e., product of number of participants and the highest numeric score [5]) to give a rank with the larger numbers meaning a greater influence on farmers' decisions to farm low spots.

Eighteen questions were designed to assess the influence of low spot size and economic situation and whether the respondent would continue to farm the low spot under each scenario. Scenario based questions have been shown to relate better to respondents actual decision-making process and stimulates respondents to think about their actions (Utomo et al. 2020). I varied the size of low spots (2, 5, and 20 acres) and for each size variation of the low spot I varied the economic situation to one of the six following scenarios. The first economic scenario stipulated that the respondent had a financial loss in three of 10 years and broke-even (i.e., $0 profit) the remaining seven years of the 10-year scenario period. The second economic scenario stated five years of loss and five years of breaking-even. The third economic scenario stated 10 years of loss on the low spot. The fourth economic scenario stated that the respondent made money on three years and had a financial loss on the remaining seven years of the 10-year scenario period in a low spot. The fifth financial scenario stated that money was made in five years and money was lost in the other five years. The last scenario stated that money was made from the low spot in all 10 years.

I also asked questions about yield rather than profit for a couple of reasons. First, I wanted to keep the number of questions low as to not overwhelm the respondent. Also, profit is directly influenced by crop yield (Sherrick 2012) and therefore would have likely been redundant response given the assumption that there was a harvestable crop available; meaning that the planting inputs were not lost to a drown out of the seeds or crop planted. Second, farmers may have a better sense of average yield per acre than profit per acre.

Comment Sections

Many respondents in addition to answering the questions also self-reported (e.g., in the electronic form) or agreed to let me document their comments (e.g., comments made to me during interviews). I used word clouds made with the “wordcloud” package (Fellows 2018) in program R to construct word diagrams that emphasized important terms or concepts from the comment sections based on the frequency of words from the input. Word clouds are useful when assessing qualitative data to recognize themes (Jaeger et al. 2022). Word clouds helped to quickly visualize common words from the comments and to relate them to lines of questions in this study.

Results and Discussion

Any broad statements made about farmers in the discussion are made in reference to the respondents of the survey questionnaire. I was unable to attain a large enough sample size of participants to assume that the respondents to this survey completely represent the target population of North Dakota farmers. Also, these respondents may represent a more conservation friendly cohort of North Dakota farmers because of the large percentage of them that were originally contacted for another study I conducted where they allowed bird surveys on their wetlands or because they responded to the opt-in web survey.

Respondent and Farm Characteristics

I conducted eight interviews and received 10 online opt-in responses from the online questionnaire distributed through a grain association's newsletter. The number of respondents was relatively low but was not unexpected given the online delivery method and the target population (Pennings et al. 2002). Most respondents self-identified as a decision maker (n = 10), operator (n = 10), owner (n = 17), and/or a person who rents land from another to farm (n = 5, Appendix E (Figure E.1)). Respondent age ranged from 30–70 years with a median age of 56 years (Appendix E (Figure E.2)). Most respondents (78%, n = 14) were married and had one to five children (89%, n = 16). About 77% (n = 14) had achieved college or technical school education with the remaining having a high school education.

Field topography was described as gently rolling (44%, n = 8), rolling (28%, n = 5), or flat (28%, n = 5). The total hectares (ha) farmed ranged between 389 and 3,642 (960–9,000 acres) with a median of 1,619 ha (4,000 acres). Only one participant did not rent at least some land owned by someone else to increase their own farming operation land area. The other 17 participants rented between 65 and 2,428 ha (160 and 6,000 acres) for farming. One respondent rented-out land (65 ha, 160 acres) to someone else for farming. Further mention of units of measure for land area will use acres because that was how the questions were presented and is how many farmers in North Dakota think about their operations.

Most respondents (89%, n = 16) reported that the >75% of their income was from farming. Respondents employed 1–7 employees with a median of three employees. Only two farmers reported that they did not employ family members while most reported employing 1–6 family members with a median of two family members employed.

Respondents reported using yield monitors (78%, n = 7), variable-rated (VR) planting (61%, n = 9), VR spraying (28%, n = 4), VR fertilizer (6%, n = 1), prescription maps (61%, n = 9), and auto-steer (6%, n = 1) technologies in their farming operation (Appendix E (Figure E.3)). Reported corn yield ranged between 6.3 and 12.6 Mg/ha (100–200 bushels [bu] /acre, Table 5.1) with a median of 9.1 Mg/ha (145 bu/acre). Soybean yield was reported between 1.4 and 6.2 Mg/ha (20 and 47 bu/acre) with a median of 2.6 Mg/ha (35 bu/acre). Wheat and sunflower yields were also reported (Table 5.1).

Table 5.1. Yields ranges and medians for commonly reported crops from survey respondents. Yields are reported in megagrams per hectare (Mg/ha) and bushels or pounds per acre (bu/acre or lb/acre).

	Number of Respondents	**Range (Mg/ha)**	**Median (Mg/ha)**	**Range**	**Median**
Canola	5	2.2–4.0	2.6	2000–3600 lb/acre	2300 lb/acre
Corn	11	6.3–12.6	9.1	100–200 bu/acre	145 bu/acre
Barley	3	4.3–5.4	3.0	80–100 bu/acre	85 bu/acre
Soybeans	17	1.4–6.2	2.6	20–47 bu/acre	35 bu/acre
Sunflowers	1	–	2.2	–	2000 lb/acre
Wheat	14	2.4–5.4	3.8	35–80 bu/acre	56 bu/acre

Behaviors and Attitudes

Four farmers (22%) reported that they had 'never' enrolled in a conservation program (Appendix E (Figure E.4)). Eleven farmers (61%) reported that they had enrolled but were unsure of the programs in which they had enrolled. Six farmers (33%) had enrolled in the Conservation Reserve Program (CRP), Conservation Stewardship Program (CSP, 28%, n = 5), Environmental Quality Incentives Program (EQIP, 22%, n = 4), and one farmer (6%) had enrolled in the Working Wetlands Pilot Project (WWPP).

Question 6 (Appendix D), referred to how many acres of low spots the respondent actively managed (i.e., burned, disked, mowed, or sprayed) during dry, average, and wet years, respectively (Appendix E (Figure E.5, E.6, E.7)). I would have expected that during a dry year, more wetland/low spot areas would have been actively managed because the water level in these areas would have been low enough to allow farmers to get machinery into these spots. Inversely, wet years would not allow machinery into these areas and reduce the acres actively managed. However, some of the online respondents may have misinterpreted this question because low spot acres managed increased when comparing dry-year to wet-year managed low spot acres, whereas the opposite was true for most interview participants. One online respondent actively managed "0" area under both dry and wet years. Three other online respondents reported managing more low spot area during wet years than dry years with an increase of 36.4–283.3 ha (90 to 700 acres). Most respondents (72%, n = 13) did have a decrease in acres managed when comparing area managed during dry to wet years. The increase in acres from the online respondents may be a reflection of an increase in total wet acres rather than actively managing (e.g., disking) the wet areas themselves. Rewording of the question may have remedied this, however the preamble to the questionnaire specifically stated the areas in which I was interested.

Yet, this may also indicate that farmers, even during wet years are attempting to address high water levels on their crop fields rather than waiting for dryer years to attempt to use the land.

Similarly, question 7 (Appendix D) compared dry, average, and wet years in relation to how much area of low spots the farmers reported getting planted/seeded (Appendix E (Figure E.8, E.9, E.10). I expected the amount of seeded or planted area to increase in dry years and decrease in wet years and this was what the respondents reported. Again, one respondent reported to not seed any of low spot areas no matter what the yearly water conditions were. All others decreased the amount of seeded area during wet years between 29%-100% compared to dry years.

The overall amount of low spot area managed or seeded was higher than expected. However, there has been a large increase in the water levels of wetlands in North Dakota over the past 30 years as North Dakota went into an extended wet period (McCauley et al. 2015). Given the age of some farmers, these numbers might be representative of the change in area from the 1980's when the region was drier compared to the wet period beginning in the early 1990's and continuing in recent years (Huang et al. 2011). This sentiment may also be felt by more recent generations based on a respondent comment from this survey:

> "More than 1/3 of owned acres will be under water next year. Dad had 320 acres in an area but can now only farm 150 due to high water."

Factors Affecting Cultivation of Low Spots

The most influential factor affecting farmers' decisions to attempt to farm a low spot was the ability to get machinery into the area (Figure 5.1). A common theme related to this factor was in the word cloud from all the 'decision factor other' comment section of the survey, which was "try" (Appendix E (Figure E.11)). Essentially, most respondents plan to farm all the ground they can, feel inconvenienced when areas need to be driven around, or want to reduce soil compaction that they feel happens when areas get driven over multiple times (Leitch 1980; Leitch 1983; Cortus et al. 2009; Cortus et al. 2011). Themes from other comment section word clouds were mentioned here as well, such as “efficiency” (Appendix E (Figure E.12, Table E.1)). Some respondents stated as such in the comment sections of this questionnaire:

“Reduce the number of headlands for row crop operations.”

Headlands refers to the area of planted land where the rows of one direction of planting intersects another and usually results from multiple turns around or by an obstacle, such as the field boundary or wetland boundary, that causes a different row pattern than is the typical straight line within the field. Headlands are also commonly made around the edges of crop fields.

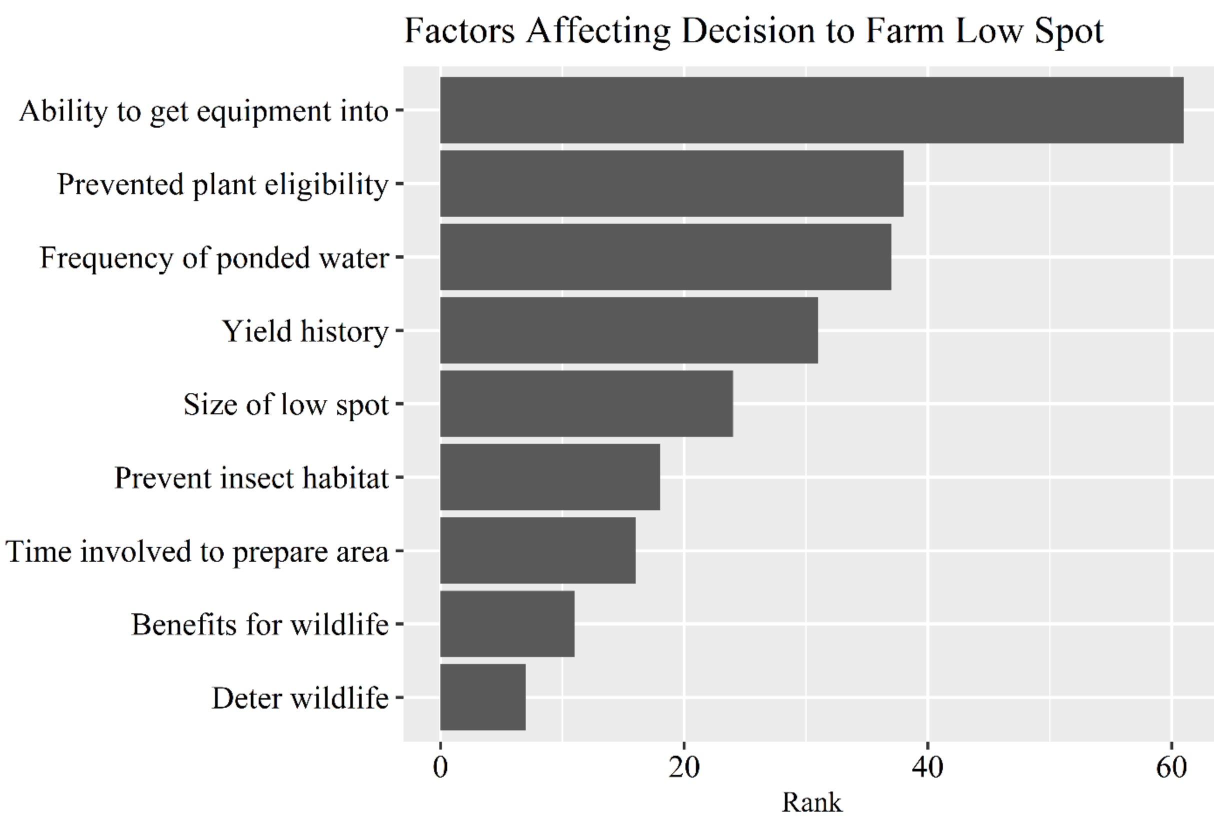

Figure 5.1. Ranking of listed factors that potentially influenced farmers’ decisions on whether to farm a low spot. Higher ranking scores indicates a more important factor to respondents that influenced their decisions to farm a low spot.

> “In wet years, farming efficiency is cut in half because the operations end up circling spots.”
>
> “Some of the reasons we’re willing to lose on those spots also has to do with efficiency (turning, slowing down, etc..)”
>
> “Number 1 – Cropping low areas greatly increases efficiency and yields. Also, soil health is much better by reducing compaction caused by going around areas”
>
> “Owner doesn’t care about the money. If wetlands are dry, then they will work them.”
>
> “More likely to farm a small wet spot rather than drive around it.”
>
> “Also depends on the position of the wetland within the field, i.e., whether it's on the edge and easier to go around or in the middle when you have to go around all sides. Sometimes better to just go through the wetland than drive around, especially with a corn crop.”

The second most prominent factor noted to influence respondents’ decision to farm a low spot was to try to keep the ground eligible for prevented plant insurance (Figure 5.1). Prevented plant insurance provides financial protection based on pre-planting costs of an insured crop if certain weather conditions such as flooding prevent a crop from being planted on land that has previously been planted and harvested (USDA, Risk Management Agency). Prevented plant insurance is administered by the US Department of Agriculture’s Risk Management Agency and has stipulations such as eligibility requirements for land, i.e., the “land must be planted, insured, and harvested in at least one of the four most recent crop years”.

Prevented plant insurance was a prominent word paraphrased in my comments from the interview portions of this questionnaire (Appendix E (Table E.2, Figure E.13)). Below are some quotes from the interviews involving prevented plant insurance:

> In reference to another question, “If lost money 10/10 years, then the ground is just bad. Farming a 20-acre low spot has more to do with keeping up prevent plant acres and bad ground likely due to salt issues. Prevented plant gives false hope and is incentivizing farming poor ground.”
>
> “Prevented plant is a vicious cycle. Used more for purely money making. Prevented plant factors into renting especially. Prevented plant would be better if it was more limited.

Maybe an option could be something including an alternative such as drain tile. Better to address the situation directly through drain tile than to use a bandage like prevented plant insurance. … People will do whatever to reset prevented plant insurance such as drop seed count really far down. Prevented plant check this past year was enough to cover all premiums of their insurance."

"Had 800 acres of prevented plant insurance this past year, which was more than ever. Insurance dates come into play. …One reason is because the farmer has to make a good faith attempt to farm."

"Depends on prevented plant laws. Prevented plant is the difference in these low spots."

The third most selected factor influence the decision to attempt to farm a low spot was the how frequent the low spot has been wet in the past. Additional respondents' comments related to frequency of ponded water within low spots are listed below.

"The gut feeling of worth the time and effort to disturb dried up wet area or is odds of just drown out again greater."

"What the potential is for the wet spot to flood out during the growing season."

This statement is likely to rely on water ponding history that the respondent associates with the area. Also, pertinent to this response was the following comment:

"What crop might get seeded in the low spots for the field."

The comment immediately above, refers to the often-utilized practice where crops that have shorter maturity dates can be planted later in the spring. For example, soybeans have a shorter maturity length and can be planted near mid-May in North Dakota, whereas corn has a longer maturity length planted in late April or early May (Kandel and Endres 2019; Ransom 2019). Soybeans and corn are also more susceptible to water events at different times of their maturity (Çakir 2004; Morrison et al. 2006; Kandel and Endres 2019). Corn has been shown to have higher frequencies of loss than soybeans in wetland areas (see Chapter 3).

Other factors such as farming the low spot to prevent insect habitat, yield history, and size of the low spot fell in the middle of the rankings for influence on decisions to attempting to farm low spots (Figure 5.1). The lowest two factors involved attempting to farm low spots to keep wildlife out of them (lowest consideration) or not farm low spots for the benefit of wildlife (Figure 5.1).

> "#2 control weeds, many times this will be the start of a Canadian thistle patch as waterfowl bring in seed."
>
> "The wet areas must be worked as often as possible, or they are permanently lost to the wildlife groups that have no interest in farm succeeding."
>
> "I would like to see a study using a couple different methods on these low wet spots. Make a pond and the dirt removed raise an area one-two acres above flood elevation and plant to deep rutted trees. Pond for evaporation and wildlife and same with the trees that use subsoil moisture and can be used by wildlife. We need to look at these spots with a long-term agenda to save this ground for future generations."
>
> "Wildlife adapt to what habitat/cover there is."
>
> "Likes wildlife and wetlands."

More responses were listed in the "other" section of the factors influencing decisions to farm low spots and were related to reducing snow catch, weed establishment, and soil compaction (Appendix E (Table E.3)). Below is a relevant interview comment regarding factors effecting the decision to farm wetlands on rented land:

> "Paying rent on land and if nothing is done with those then you have already lost money. There are 2 sides to it though, i.e., to what extent do you want to improve land that you rent? May end up talking to the renter and asking if they would take the unproductive land out of the agreement. They may or may not. It's in own best interest to get into all rented land. May have to do more such as weed control even if you get the wetland seeded."

Yield and Cost Comparisons

Most respondents (89%, n = 16) reported yields when harvesting in low spots to be "about the same", "higher", or "a lot higher" than yield in the surrounding field and six respondents reporting yield as "a lot higher" (Figure 5.2). This question assumes the preparation and planting was done and a harvestable crop was available. The perception of higher yields from respondents may be true under drier conditions (Chapter 4), but on average-water condition years this was not found to occur in Chapter 4 or in literature review.

> "Dry years, wet areas = Higher yield. Opposite on wet years."
>
> "They've found organic matter to have the highest correlation to increased yields"
>
> "Yield varies by year. Dry year will outperform the rest of the ground. Average or wet year will be same or a little less. Might have some quality issues."

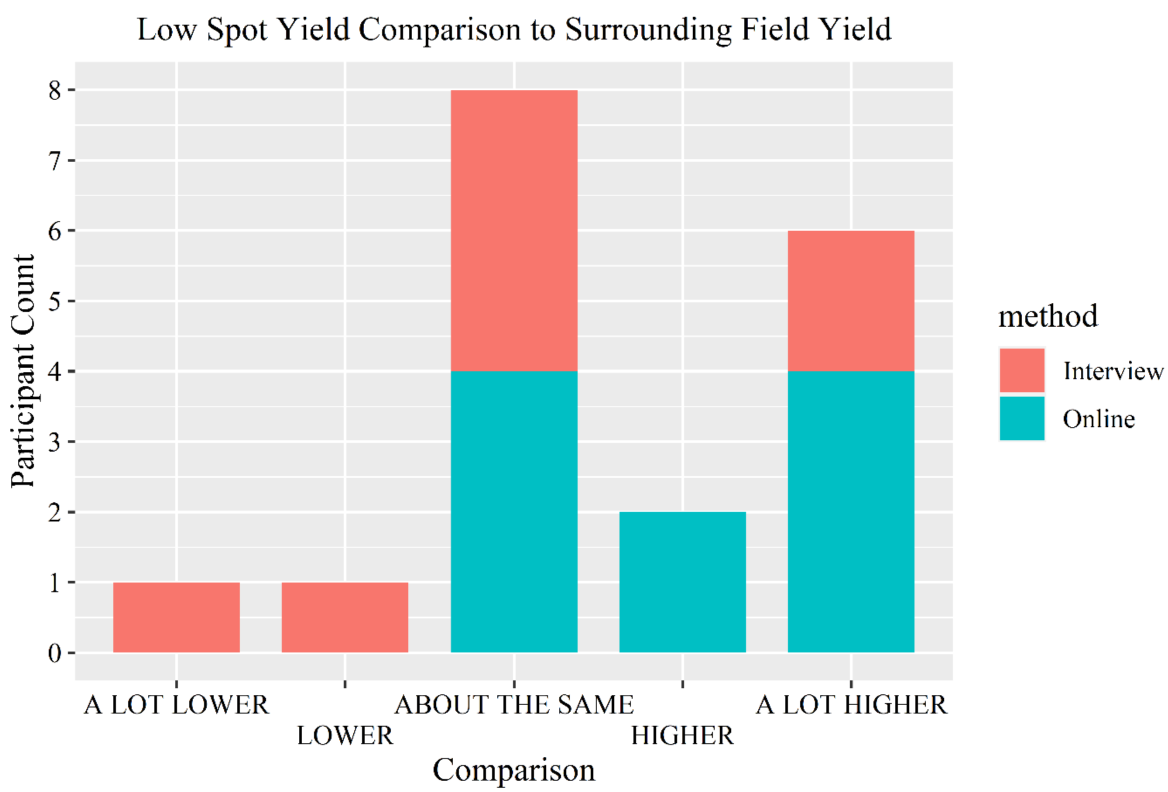

Figure 5.2. Count of respondents' choices as to how yield harvested from a low spot compares to yield harvested in the surrounding field. Colors indicate survey delivery method.

Two other studies conducted in Iowa and Alberta, Canada found that yields and profit are less in wetland areas (Fey et al. 2016; Clare et al. 2021). Clare et al. (2021) reported 56% of drained and consolidated wetland basins for the one year study resulted in a financial loss for the farmers. One of the farmers in the study had financial losses in 90% of their drained and consolidated basins. Fey et al. (2016) reported that in four of nine years, pothole wetland in Iowa had economic losses and in only one year (drought year) was the return on investment higher in pothole areas. Chapter 4 of this dissertation found that during the driest conditions soybeans may be higher in profit in planted wetlands than upland areas but are similar at average water conditions and less profitable during the wettest conditions depending on which costs are included in profit calculations. Corn profit under the driest conditions was similar to uplands but significantly less at average water conditions and far less profitable than uplands during the wettest conditions.

The respondents were asked to compare the cost to prepare a low spot to preparing the surrounding field for planting (Figure 5.3). Most respondents (56%, n = 10) reported the cost of preparing low spots for planting was "higher" than the surrounding field, whereas 28% (n = 5) reported the costs to be "about the same" and 17% (n = 3) reported the costs as being "a lot higher". I could not find literature estimating cost comparisons for preparing wetlands for planting. However, personal communications with farmers and general observations from conducting another study (Chapter 2) made evident that more effort (i.e., multiple passes when disking or combinations of manipulations) was given to achieving a similar land manipulation (i.e., burning, disking, or mowing) result as the surrounding field which was typically only disked with a single pass with machinery. Effort would likely increase when longer idled (i.e., farmed around) periods occurred for a wetland which could allow more dense vegetation to grow compared to a wetland that may get farmed more frequently. Some farmers will wait for wet spots to dry and come back at a later date to seed them.

> "Our fields are well drained, so we probably do not make sense to include in this survey. On a wet year we may have to seed around a wet spot but are usually able to come back and seed it at a later date."
>
> "Weeds plug digger so may have to mow first."

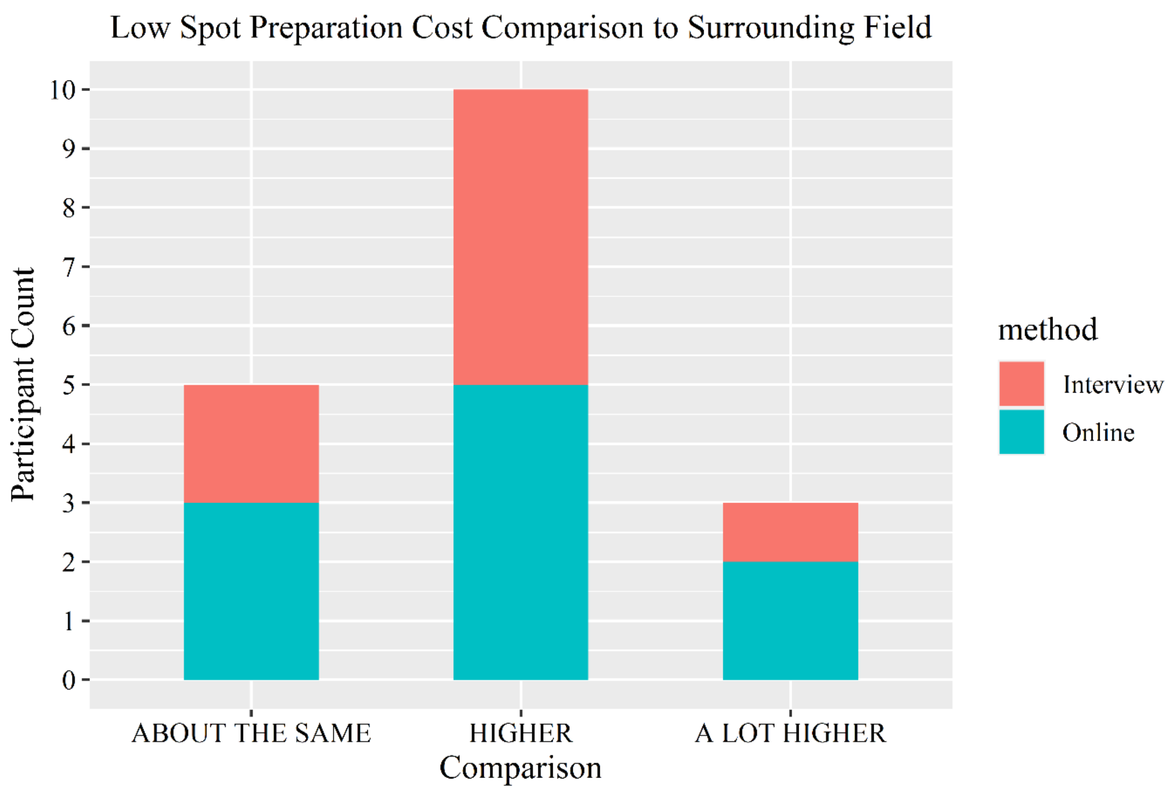

Figure 5.3. Count of respondents' choices as to how costs to prepare a low spot for planting compares to yield harvested in the surrounding field. Colors indicate survey delivery method.

Likelihood of Planting or Harvesting Low Spots

Two questions (9–10, Appendix D) inquired about the number of years out of 10 years that the respondents assumed that they could either plant or harvest a crop in a low spot. The preparations required prior to performing the action (i.e., planting or harvesting) of the question had already occurred in this scenario. For example, when this question regarded planting, the area had already been prepped (e.g., disked) and was ready to be planted. Likewise, when the question regarded harvesting, the question stated that the area had been prepped and planted previously.

When asked how many years out of 10 the respondent could get a low spot planted after it was prepped, 50% ($n = 9$) of respondents chose between 3–5 years out of 10 years (≤50% of the time) that they assumed they could get that area planted (Figure 5.4). The other 50% of respondents selected between 6–9 years of a 10-year period that they assumed could get a low spot planted. The most selected number of years out of the 10-year period the responded assumed they could plant the area was 5 years (n = 5).

When the same question was posed regarding years that they could harvest the low spot, 56% of respondents (n = 10) selected between 2–4 years that they assumed they could get a harvest from a planted low spot (Figure 5.5). The other 44% of respondents selected between 6–10 years they could get a harvest from a low spot after it had been planted. The most selected number of years out of a 10-year period the respondent assumed that they could harvest the low spot was 3 years (n = 4).

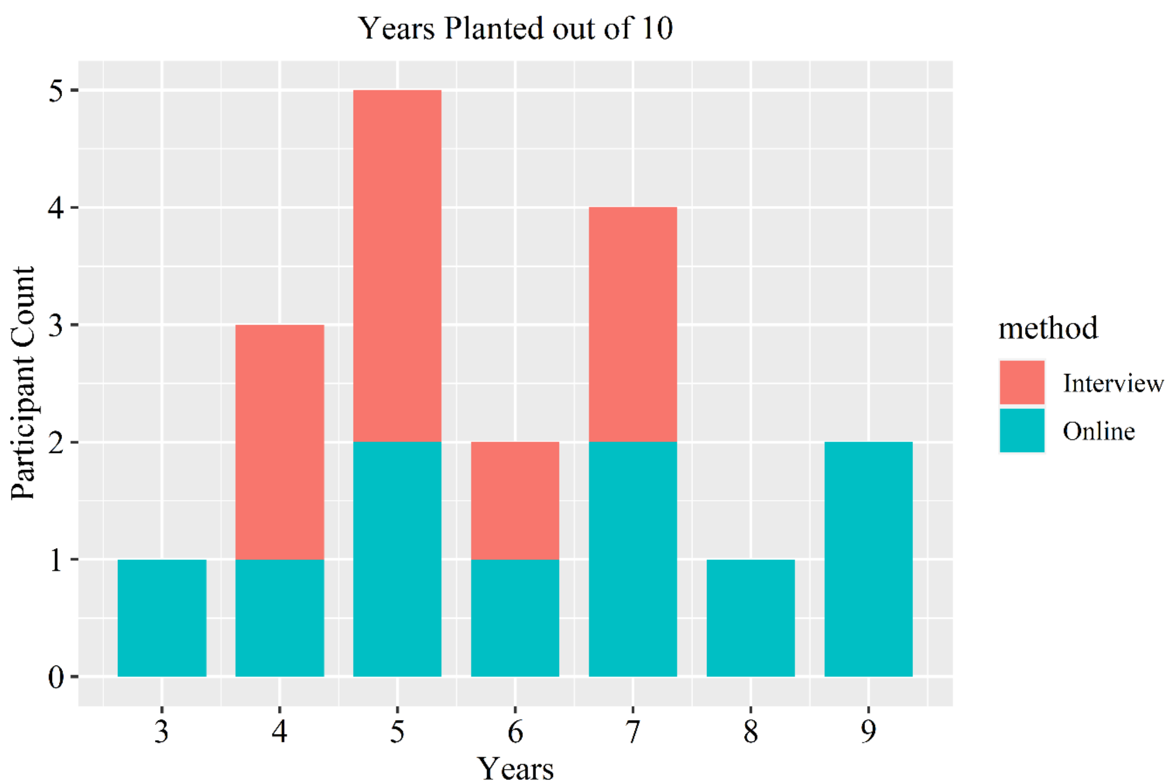

Figure 5.4. Count of respondents' choices as to how many years out of 10 that they felt conditions would allow them to get a low spot planted, given the area was already prepared for planting (i.e., disked). Colors indicate survey method.

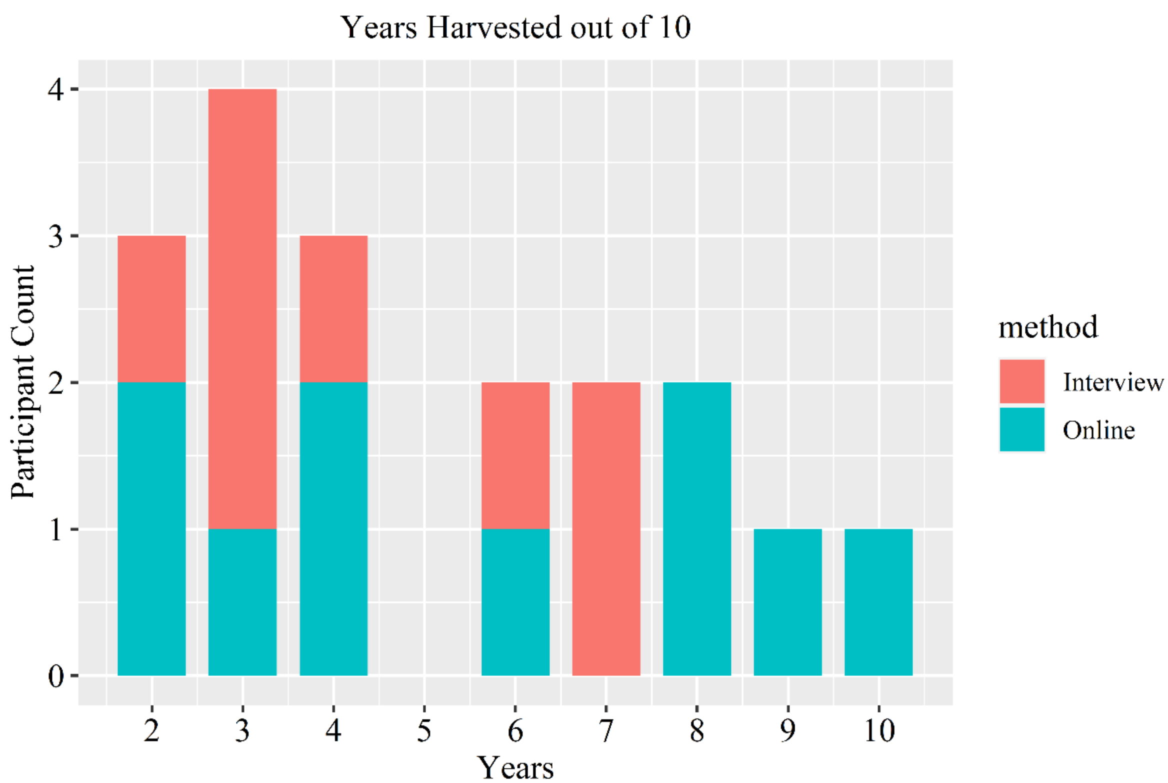

Figure 5.5. Count of respondents' choices as to how many years out of 10 that they felt conditions would allow them to harvest a crop from low spots given that it was already planted. Colors indicate survey method.

Wetland Size and Financial Scenarios

In a scenario with negative net revenue (i.e., financial loss) in three of 10 years and zero net revenue (i.e., broke-even) in seven years, 94% (n = 16) of respondents would continue to farm a 2-acre and a 5-acre low spot (Figure 5.6). On a 20-acre low spot, 88% (n = 15) of respondents would continue to farm the low spot given the economic and size scenario. For this question, one responded for each size variation did not respond and was removed from the percentage calculations, which is also how subsequent non-response will be addressed.

In a scenario with a financial loss in five of 10 years and broke-even the remaining five years, 82% (n = 14) of respondent would continue to farm a 2-acre and a 5-acre low spot (Figure

5.6). On a 20-acre low spot 72% (n = 13) of respondents would continue to farm the low spot given the economic and size scenario.

In a scenario with negative net revenue from farming a 2-acre low spot in all 10 years, 39% (n = 7) of respondents stated that they would continue to farm the low spot (Figure 5.6). On a 5-acre low spot with financial loss all ten years, 67% (n = 6) of respondents would continue to farm the area. The 20-acre low spot scenario had one non-response and 29% (n = 5) of respondents that would continue to attempt to farm the low spot.

In a scenario when money was made in three years but had a financial loss in the remaining seven years, 78% (n = 14) of respondents would continue to farm a 2-acre low spot (Figure 5.7). For a 5-acre low spot under the same financial scenario, 67% (n = 12) of respondents would continue to farm it while 61% (n = 11) would continue to farm a 20-acre low spot.

In a scenario with positive net revenue in five years and negative net revenue in the remaining five years, 100% (n = 17) of respondents would continue to farm a 2-acre and a 5-acre low spot (Figure 5.7). On a 20-acre low spot under the same economic scenario, 88% (n = 15) of respondents stated that they would continue to farm the area.

In a scenario with a positive net revenue in all ten years, 100% of the participants would continue to farm a 2-acre low spot (n = 18, Figure 5.7). Under the same economic scenario, with a 5-acre and 20-acre low spot, 94% (n = 16) of respondents stated that they would continue to farm those low spots.

The scenario-based question results seem to show that wetland size would play a role in some farmers' decisions to attempt to farm within them. Continuing to farm the smaller low spots is likely in a perceived effort to increasing efficiency by driving through rather than around the low spot (Cortus et al. 2009; Clare et al. 2021). However, at least five respondents would continue to attempt to farm any sized low spot up to 20 acres even when they incur financial loss 10 out of 10 years. For some, if they are renting then they already pay for those areas and feel the need to continue to attempt to farm the as much of the rented land as possible including the low spots.

The percentages of respondents that would continue to farm low spots, regardless of size, for the made-3-lost-7, made-5-lost-5, and the made-10 scenarios were 69%, 96%, and 96%, respectively. The percentages of respondents that would continue to farm low spots, regardless of low spot size, for the lost-3-even-7, lost-5-even-5, and lost-10 scenarios were 92%, 79%, and 35%, respectively. This result was expected given that higher consistent losses would deter some farmers from attempting to farm these areas and the inverse is true regarding consistent profits. However, there is a base of respondents (35%) that would farm low spots regardless of the financial situation for reasons previously discussed in this study (Figure 5.7).

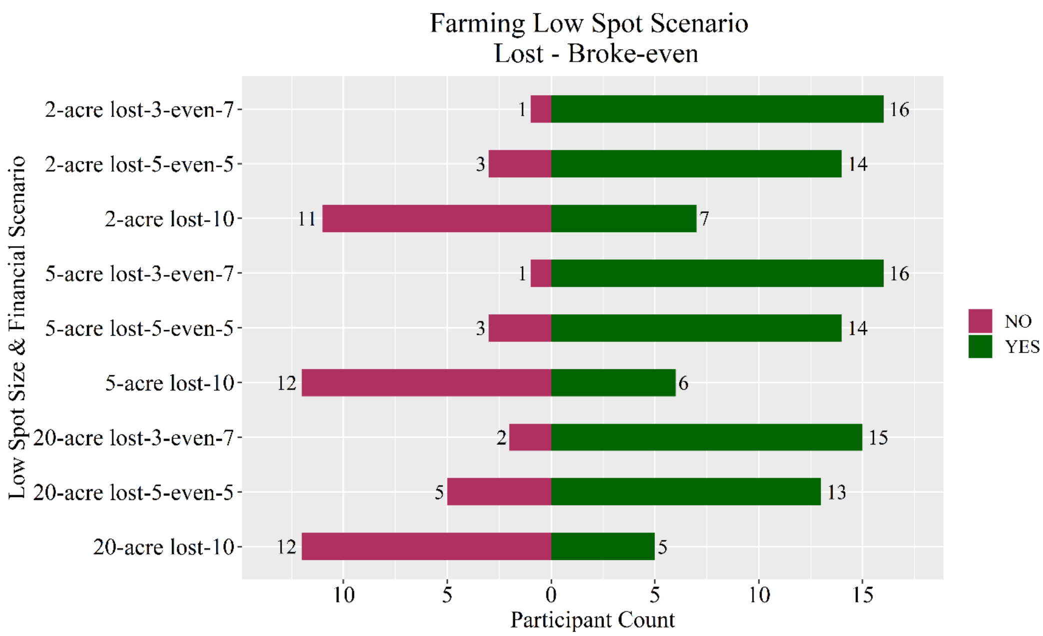

Figure 5.6. Count of participant responses as to whether they would continue to farm a low spot given the size and the financial history of farming the low spot. “NO” responses are counted to moving left from ‘0’ while “YES” responses are counted moving right of ‘0’. The financial scenarios are based on incurring a financial loss in the low spot for 3, 5, or 10 years while breaking even for the remaining years of a 10-year period, so 7, 5, or 0 years, respectively.

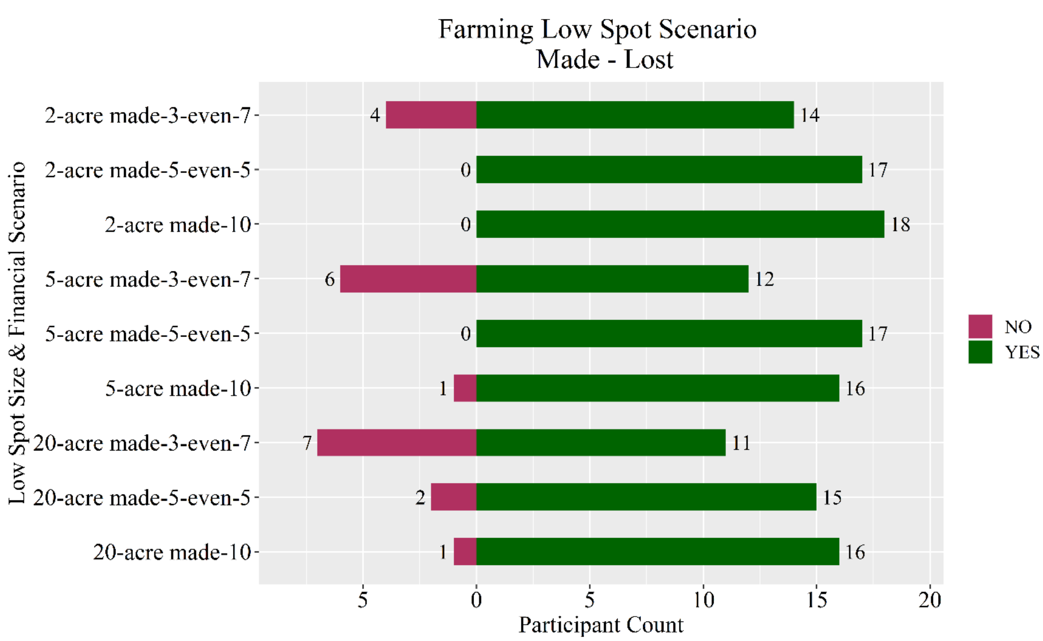

Figure 5.7. Count of participant responses as to whether they would continue to farm a low spot given the size and the financial history of farming the low spot. “NO” responses are counted to moving left from ‘0’ while “YES” responses are counted moving right of ‘0’. The financial scenarios are based on having a financial gain in the low spot for 3, 5, or 10 years while breaking even for the remaining years of a 10-year period, so 7, 5, or 0 years, respectively.

Limitations and Challenges

There are multiple challenges with conducting surveys with farmer including interviews and online questionnaires, such as respondent bias, population cannot be accurately described, unknown response rates, cost of multiple surveys, and timing of surveys (Pennings et al. 2002; Wright 2005; Andrade 2020). This study had low participation which limits the study's applicability to a larger population. The survey was conducted at the start of the COVID-19 pandemic which eventually limited solicitation of interview participants. This issue was compounded by the decrease of available home phone numbers to contact or respondents that would answer unknown phone numbers identified by caller id technology (Kempf and Remington 2007). These issues should be considered in future work.

Implications and Conclusions

The low number of respondents to this survey makes it difficult to extrapolate to the larger target population of Drift Prairie farmers. A larger group of respondents would need to be surveyed to accurately reflect the target population. However, there are some key takeaway points that may be useful in the context of future surveys or conservation programs.

Some concepts from this study could help to inform a conservation program and promote mutually beneficial outcomes for farmers and conservation efforts. The ability to get equipment into a low spot, which was the highest ranked decision factor in whether to farm low spots, is an important result. Farmers are likely making these decisions while at the low spot in their farm machinery and it logically follows that if it was dry enough that they would farm the area because there is little or no present physical limitation preventing cultivation. Many reasons for continuing to farm low spots were left in the comments, such as reducing compaction caused by multiple passes when circling a low spot with machinery or the nuisance of driving around the low area. However, there still remains the risk of planting a crop and high enough precipitation to pond water and kill the plants or seeds (DeBoer and Ritter 1970; Lizaso and Ritchie 1997; Sullivan et al. 2001; Zaidi et al. 2004)

Another important decision factor was to farm the low spot to keep the area eligible for prevented plant insurance. This concept was prevalent in the interview portion of this study. Prevented plant insurance can provide a considerable amount of compensation for farms. One participant, not during an interview, stated that for one farming season, all of the profit for the farm came from prevented plant insurance payments. A conservation program may need to be cognizant of prevented plant insurance and examine how a program and prevented plant insurance would fit together.

Another takeaway was that there may be an influence of low spot size on whether some of the respondents attempted to farm a low spot. This concept may need to be explored more because it has implications on a conservation program costs if farmers would be compensated on a per acre basis. There may be a size threshold that would be beneficial to find where the return on investment is maximized for a conservation program but is also beneficial for the farmer. Size of wetland has been an influencing factor in other studies (Wachenheim and Devney 2018).

The always-farm-low-spots behavior which was a sentiment held by about a third of respondents, needs to be acknowledged when developing conservation programs. Farmers who behave similarly to the always-farm-low-spots respondents of this survey likely are not motivated enough by monetary gain for them to change their behavior or would not be affordable for a conservation program at their required compensation level. Most other farmer groups might be more enticed by a conservation program that emphasizes the financial gain of a conservation program than by emphasizing the environmental benefits (Sweikert and Gigliotti 2019).

However, their perceptions of the low spot yield to surrounding field yield comparisons may be misguided or misrepresented. In Chapter 4, yield estimates were only "about the same" or "higher" on the driest estimated years for soybeans, but were lower for corn, which may be an indication that farmers expect higher yields from low spots than actual realized yields. As Clare et al. (2021), stated in their profit study, farmers underestimated the magnitude of loss in drained and consolidated wetlands. Yet, many respondents to this questionnaire stated they use at least one type of precision agriculture technology, with many using variable rated seeding and over a third using yield monitors, all with the presumed intent to be more profitable across their operation. However, almost a third of the respondents would continue to farm low spots regardless of the financial scenario or low spot size, even if they were to incur 10 consecutive years of financial loss. This suggests a few things — that respondents may not be examining their precision agriculture data closely and do not know subfield level yields or profits for low spots or they are more motivated to farm low spots because of the perceived loss in efficiency, the inconvenience of driving around low spots, or have other, potentially social (Prokopy et al. 2008; Baumgart-Getz et al. 2012; Rose et al. 2018; Villamayor-Tomas et al. 2019), factors that have strong effects on their behavior. Future studies similar to Clare et al. (2021), Fey et al. (2016), and Chapter 4 of this dissertation conducted in other areas where wetland conservation is a high priority may be beneficial to conservation programs to understand and disseminate to farmers what long-term profitability is within wetlands from additional areas of North Dakota. Also, the perceived loss in efficiency around low spots, and associated soil compaction resulting from repeated machinery passes, may be an area that needs a better understanding through quantifiable examination which could be done using precision agriculture data. Additionally, exploring social factors that influence farmers behaviors regarding low spots may also be beneficial to help enrollment into conservation programs and help farmers make more profitable decisions related to low spot areas. Many studies have found that social groups have a large influence on adoption of new practice or program by farmers and suggests the use of peer groups to help inform other farmers (Rose et al. 2018).

Private landowners are the largest group of people that manage land in the US and can greatly impact the direction of wildlife populations and conservation efforts in the future. Having flexible conservation programs for landowners may be beneficial to reaching conservation goals (Sweikert and Gigliotti 2019). A reoccurring theme in the literature when developing new programs is the want and need for landowners to be involved with conservation planning and development of conservation programs (Wachenheim and Devney 2018; Sweikert and Gigliotti 2019). Therefore, including farmers, because they want to be involved and they influence their peers, can help adoption of a program and possibly change attitudes towards low spot or wetlands areas but also may give a program the best potential to succeed.

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CHAPTER 6. GENERAL CONCLUSION

Conservation efforts, especially those intended to benefit waterfowl, often focus on preserving nesting cover through protecting native grasslands or restoring cropland to grassland cover. While these efforts are beneficial to waterfowl and other species, they may require willingness of landowners to remove large areas of their lands from crop production for financial compensation that is less than would be obtained through continual crop production. Many hectares of cropland remain in production in the Prairie Pothole Region (PPR) that provide little nesting habitat for waterfowl (Rischette et al. 2021) but should not be overlooked because the wetlands within PPR cropland may still provide some ecosystem services, such as foraging habitat. For example, in the Drift Prairie, a physiographic region within the PPR, its estimated that more than 80% of temporary and seasonal wetlands are located within crop or alfalfa fields (Niemuth et al. 2006). Wetlands of the PPR provide crucial foraging habitat for migrating shorebirds and waterfowl refueling on their migration routes (Batt et al. 1989; Cox et al. 1998; Hegyi and Sasvari 1998; Euliss and Mushet 1999; Krapu et al. 2006; Anteau and Afton 2009). Therefore, understanding the contributions of PPR wetlands to both natural ecosystem services and to farming operations is vital to their conservation.

Understanding how waterbirds use wetlands within crop fields is a first step toward identifying ecosystem services wetlands provide. Wetlands surrounded by cropland are no longer exposed to many of the natural disturbances which would reduce the amount of vegetation in the basin and has resulted in many wetlands with dense stands of vegetation (DeKeyser et al. 2003; Bansal et al. 2019). When soil conditions are dry farmers will manipulate these areas with machinery to prepare them for spring planting as conditions allow. In Chapter 2, I found that manipulations such as burning, disking, mowing, or harvesting vegetation or crops within wetland reduced the height of vegetation within inundated areas of the wetland compared to idled (i.e., unmanipulated) wetlands. Burning, disking, and harvesting also reduced the proportion of vegetation coverage in the inundated area. Whether management method or vegetation characteristics were more important varied by species. Therefore, certain manipulation techniques may have affected an aspect of the system that was unmeasured, but the overall result for waterfowl was that many species preferred low to mid-levels (~0–0.40) of vegetation coverage in agricultural wetlands. My results suggest that leaving agricultural wetlands idled for too long allows dense stands of vegetation to form and reduces occurrence probabilities or densities of shorebirds and waterfowl. Shorebirds typically prefer more open habitats (Skagen and Knopf 1994; Niemuth et al. 2006; Skagen et al. 2008) while dabbling ducks tend to prefer a moderate amount of vegetation coverage in other non-cropland areas (Smith et al. 1964; Weller and Spatcher 1965; Weller and Fredrickson 1973; Murkin et al. 1982; Pearse et al. 2011). Drift Prairie wetlands evolved with periodic natural disturbances from which they are now cut off because of the modern segmented landscape. The wetlands in the current landscape, especially isolated agricultural wetlands, may need periodic mechanical or pyric disturbances to increase use by migrating shorebirds and waterfowl for foraging habitat services.

Although wetlands are often noted for their ecosystem services (Kirby et al. 2002a; Kirby et al. 2002b; Gleason et al. 2008; Brinson and Eckles 2011), their contributions to direct use by humans are often forgotten or described in the context of intrinsic, aesthetic, or recreational value. When wetlands are assigned a value in an agricultural scenario is frequently in the form of cash rent or an abstract monetary value of someone's willingness to pay for its ecosystem services. A utilitarian, and possibly more direct measure, of a wetland's contribution to agricultural ecosystem services is its ability to produce a crop. I found that over half of temporary wetland area and nearly one third of the seasonal wetland area is planted on average through examining 19 years of precision agriculture data (Chapter 3). However, these areas also had higher frequencies of financial loss than corresponding upland areas (Chapter 3 and 4). Similar results were found in other pothole wetland studies in Iowa, USA and Alberta, Canada (Fey et al. 2016; Clare et al. 2021). The wetlands in my study, where drainage status was not known, had similar frequencies of financial loss compared to the Iowa study which occurred in a more intensely drained area of the PPR. The Alberta study, which was comparing drained and consolidated basins to undrained wetland basins, found that undrained basins had better profit results for farmers than drained basins. My study, as well as the Iowa and Alberta studies, may be cautionary examples for farmers to not expect significantly greater financial gains or less frequency of losses from draining wetland areas for crop production. However, further, and more direct studies would need to be conducted for drained and intact wetland areas in the Drift Prairie to confirm the outcome.

Cultivating wetland areas with corn or soybean crops was profitable in average precipitation years. The yields and profits from wetland areas in the southeastern Drift Prairie often varied by the specifications and timing of the precipitation variable (Chapter 4). The early growing season standardized precipitation evapotranspiration index (SPEI) was a common variable in all profit and yield models and resulted in yields and profits from wetland-related landform features decreasing with wetter conditions while all other variables were held at their means. With average water conditions, seasonal and temporary wetlands had lower profits than uplands, the effect of which was more pronounced in corn crops than soybeans. Soybean yields and profit from cultivated portions of temporary wetlands at average SPEI conditions were similar to that of uplands. However, when the overall effect of the wetland is considered on yields and profits, those differences are increased and magnified under wetter conditions. The differences between upland profits and wetland profits may be a metric that conservation programs can use to incentivize alternative management practices that can create profitable wetland areas for farmers and more useable habitat for wildlife in croplands.

Over-winter moisture prior to the growing season also had negative effects on both corn and soybean profits, which was more prominent in wetland-related features and may be a useful predictor to farmers for crop selection and for planning sub-field variable rated planting. Precipitation patterns have been predicted to shift in the PPR (Johnson et al. 2005; McKenna et al. 2017), which may have implications for the amount and types of crops grown in the region. If precipitation patterns shift to lower summer precipitation and more extreme precipitation events in the spring, then both corn and soybeans could be affected. I found that late growing season precipitation conditions had positive effects on corn yield but negative effects on soybean yield and profit, which coincide with each crops' individual water stress vulnerabilities (DeBoer and Ritter 1970; Çakir 2004; Morrison et al. 2006).

Despite the frequency of financial loss and higher risks associated with cultivating wetlands, many farmers continue these practices. This suggests that farmers may not look closely at or aggregate data from their fields or they have other non-financial influences which factor into their decisions to farm wetland areas. I received 18 respondents to a questionnaire I administered as an in-person interview and an online opt-in questionnaire delivered through a grain association newsletter. The low number of respondents makes the results difficult to generalize to a larger population, but there may be important aspects of the results that could be explored in further study. Most respondents indicated that their main decision factor of whether to attempt to farm a wetland was the ability to get machinery into the area to do the work. Also, there were at least five participants that would continue to farm wetlands up to 20 acres despite 10 consecutive years of financial loss. Other participants did signal a potential behavioral change as size increased or with worsening financial scenarios, which may indicate that financial compensation could be effective for some to alter management of wetlands in their fields. Also, respondents were less likely to continually attempt to cultivate larger wetlands, which emphasizes the importance or furthered plight of smaller more ephemeral wetlands to remain on the landscape.

Conservation programs often involve temporary or long-term retirement of large sections of land. However, there are many wetlands remaining in cropland that are unlikely to be enrolled in a long-term land retirement contract. Understanding aspects of agricultural wetlands such as use by waterbirds, how these wetlands fit into farming operations, and how famers view the fit of these wetlands in their operation is another step toward identifying programs and practices that are beneficial for farmers. Conservationists should work with farmers to identify low producing areas that could be enrolled into flexible and profitable contracts that allow for management of wetlands by farmers to optimize the ecosystems services they provide to society. I hope the information and insights from this study can create some of these programs or make further progress towards mutually beneficial outcomes for farmers and wildlife.

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APPENDIX A. CHAPTER 2 SUPPLEMENTAL TABLES

Table A.1. Predictor variables used in this study with their descriptions, calculations, transformations, type, and bird group (B = both; D = duck; S = shorebird) in which they were used.

Name	**Description**	**Calculation**	**Trans.**	**Type**	**Bird Group**
Management Method	what type of management was used			categorical	B
Year	year of survey			categorical	B
Date	the difference of the survey date and first CANV sighting by NPWRC	date difference = CANV - survey	log, scale	continuous	B
Depth	maximum of all water depth measurements	max of 13 water depths		continuous	B
$Depth^2$	squared maximum depth	(max depth)2	squared	continuous	D
Depth .5m	average depth of the 4 0.5m from shore depth measurements	mean		continuous	S
Depth 1m	average depth of the 4 1m from shore depth measurements	mean		continuous	S
Depth 3m	average depth of the 4 3m from shore depth measurements	mean		continuous	S
Inundated Area	area using the average of 4 distance to shore measurements	$(\text{average shoreline distance})^2 * \pi$	log, scale	continuous	B
Landscape Wetlands	Number of temp & seasonal wetlands within a 1 km buffer	count		continuous	B
Mudflat Distance	cumulative distance from shoreline to dry topsoil			continuous	S
Inundated Shape	the coefficient of variation of the distance from center to shoreline in 4 directions	sd/mean	scale	continuous	B
Proportion Inundated	the coefficient of variation of the proportion of wet distance to upland	sd/mean	scale	continuous	B
Near-Shore Depth Complexity	the coefficient of variation of all 12 near-shore water depth measurements	sd/mean	log, scale	continuous	S
Inundated Area Veg Height	average vegetation height along each transect	mean		continuous	B
Inundated Area Veg Coverage	average aerial vegetation coverage proportion along each transect	mean		continuous	B
Inundated Area Veg $Coverage^2$	squared average aerial vegetation coverage proportion along each transect	squared mean	squared	continuous	D
Mudflat Veg Height	average vegetation height along each transect in the mudflat area	mean		continuous	S
Mudflat Veg Coverage	average aerial vegetation coverage proportion along each transect in the mudflat area	mean		continuous	S

Table A.2. Modeling groups with the possible predictor variables included in each group.

Model Group	Name	Variables included
1	Management	Management method (forced), year, date, depth, depth^2, near-shore water depth (1 of the 3 for shorebirds), near-shore depth complexity, inundated area, inundated shape, proportion inundated, mudflat distance, landscape wetlands
2	No management	Year, date, depth, depth^2, near-shore water depth (1 of the 3 for shorebirds), near-shore depth complexity, inundated area, inundated shape, proportion inundated, mudflat distance, landscape wetlands, inundated area veg height, inundated area veg coverage, inundated area veg coverage^2, mudflat veg height, mudflat veg coverage

Table A.3. Final candidate shorebird occurrence models resulting from the variable selection process for each model group. Bird groups are separated by a light gray highlighted row. These data include the modeling group, the number of predictor variables in each model (K), AIC_C scores (AIC_C), change in AIC_C score from the top ranked model (ΔAIC_C), model AIC_C weight (AIC_CWt), cumulative weights from the top ranked model descending to the lowest ranked model (Cum.Wt), and log likelihood (LL). Estimates were made from the selected final models in bold.

Bird Group	Model Group	K	AICc	ΔAICc	AICcWt	Cum.Wt	LL
Any Shorebird	**Management**	**8**	**253.87**	**0**	**1**	**1**	**-118.6**
	No management	3	265.53	11.65	0	1	-129.7
	NULL	1	268.70	14.83	0	1	-133.3
Killdeer	**No management**	**4**	**247.73**	**0**	**1**	**1**	**-119.8**
	Management	16	258.85	11.12	0	1	-111.9
	NULL	1	264.57	16.84	0	1	-131.3
Sandpiper	**No management**	**6**	**224.72**	**0**	**0.85**	**0.85**	**-106.1**
	NULL	1	228.91	4.19	0.11	0.96	-113.4
	Management	10	230.73	6.01	0.04	1	-104.8
Yellowlegs	**Management**	**10**	**141.23**	**0**	**1**	**1**	**-60.01**
	No management	8	152.43	11.20	0	1	-67.82
	NULL	1	184.76	43.54	0	1	-91.37

Table A.4. Estimated probability of occurrence of any shorebird and yellowlegs for each management method during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota. Included are standard errors (SE) and lower (LCL) and upper (UCL) 85% confidence limits.

Group	Management	Probability	SE	LCL	UCL
Any Shorebird	idled	0.349	0.062	0.265	0.442
	burned	0.470	0.103	0.329	0.616
	disked	0.470	0.057	0.389	0.553
	harvested	0.902	0.094	0.665	0.977
	mowed	0.665	0.166	0.404	0.853
Yellowlegs	idled	0.077	0.039	0.037	0.154
	burned	0.325	0.141	0.160	0.548
	disked	0.108	0.040	0.063	0.180
	harvested	0.818	0.114	0.600	0.931
	mowed	0.243	0.178	0.074	0.564

Table A.5. Best fit occurrence model results for any shorebird, sandpipers, yellowlegs, and killdeer during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence intervals.

Group	Variable	$\hat{\beta}$	SE	LCL	UCL
Any Shorebird	Intercept	-0.625	0.274	-1.027	-0.237
	burned	0.504	0.492	-0.206	1.217
	disked	0.504	0.359	-0.009	1.027
	harvested	2.843	1.100	1.473	4.815
	mowed	1.310	0.794	0.203	2.524
	near-shore depth complexity	0.500	0.167	0.265	0.748
	inundated area	0.481	0.176	0.234	0.743
	inundated shape	-0.308	0.163	-0.546	-0.076
Killdeer	Intercept	0.791	0.377	0.254	1.343
	mudflat veg coverage	-0.005	0.006	-0.014	0.003
	inundated area	0.666	0.180	0.413	0.932
	inundated area veg coverage	-0.019	0.005	-0.027	-0.012
Sandpipers	Intercept	-1.272	0.221	-1.604	-0.965
	inundated area	0.191	0.176	-0.059	0.450
	inundated shape	-0.309	0.194	-0.596	-0.037
	date	0.693	0.245	0.348	1.056
	2018	-0.672	0.429	-1.291	-0.047
	2019	-1.083	0.379	-1.643	-0.548
Yellowlegs	Intercept	-2.484	0.542	-3.324	-1.754
	burned	1.752	0.816	0.593	2.961
	disked	0.376	0.617	-0.499	1.292
	harvested	3.986	0.930	2.705	5.404
	mowed	1.348	1.062	-0.262	2.854
	inundated area	0.579	0.262	0.212	0.969
	2018	-0.760	0.638	-1.702	0.148
	2019	1.669	0.603	0.835	2.581
	near-shore depth complexity	0.859	0.310	0.435	1.333
	date	-1.474	0.388	-2.067	-0.942

Table A.6. Final candidate shorebird density models resulting from the variable selection process for each model group. Bird groups are separated by a light gray highlighted row. Bird groups which used a Poisson distribution instead of a negative binomial distribution are indicated. These data include the modeling group, the number of predictor variables in each model (K), AICc scores (AICc), change in AICc score from the top ranked model (ΔAICc), model AICc weight (AICcWt), cumulative weights from the top ranked model descending to the lowest ranked model (Cum.Wt), and log likelihood (LL). Estimates were made from the selected final models in bold.

Bird Group	Model Group	K	AICc	ΔAICc	AICcWt	Cum.Wt	LL
Any Shorebird	**NULL**	**10**	**728.7**	**0**	**0.74**	**0.74**	**-353.8**
	Management	11	730.8	2.13	0.26	1	-353.7
	No management	25	741.2	12.51	0	1	-341.7
Killdeer - Poisson	**No management**	**13**	**483.2**	**0**	**1**	**1**	**-227.6**
	Management	14	497.1	13.89	0	1	-233.4
	NULL	5	557.8	74.63	0	1	-273.8
Sandpiper	**No management**	**13**	**510.6**	**0**	**0.79**	**0.79**	**-241.3**
	Management	14	513.9	3.34	0.15	0.94	-241.8
	NULL	8	515.7	5.15	0.06	1	-249.5
Yellowlegs	Management	21	328.5	0	0.58	0.58	-140.6
	NULL	**12**	**329.2**	**0.69**	**0.41**	**0.99**	**-151.7**
	No management	19	337.3	8.78	0.01	1	-147.5

Table A.7. Coefficient estimates ($\hat{\beta}$) from the count portion of the best fit density models for any shorebird, sandpipers, yellowlegs, and killdeer during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence intervals.

Group	**Variable**	$\hat{\beta}$	**SE**	**LCL**	**UCL**
Any Shorebird	Intercept	-6.630	61.920	-95.765	82.506
Killdeer	Intercept	2.080	0.578	1.247	2.912
	2018	0.838	0.447	0.195	1.481
	2019	-0.075	0.470	-0.752	0.602
	proportion inundated	0.512	0.119	0.340	0.684
	inundated area veg height	-2.214	0.678	-3.191	-1.238
	depth	1.231	0.433	0.607	1.854
	date	0.421	0.128	0.237	0.605
	landscape wetlands	-0.018	0.004	-0.023	-0.012
	inundated area	-0.660	0.083	-0.780	-0.540
Sandpipers	Intercept	3.433	0.740	2.367	4.498
	landscape wetlands	-0.013	0.006	-0.021	-0.005
	near-shore depth complexity	0.694	0.272	0.302	1.085
	2018	0.125	0.590	-0.724	0.975
	2019	-1.387	0.697	-2.390	-0.384
	inundated area	-1.002	0.206	-1.298	-0.706
Yellowlegs	Intercept	0.823	1.064	-0.709	2.354

Table A.8. Candidate duck occurrence models resulting from the variable selection process for each model group. Bird groups are separated by a light gray highlighted row. These data include the modeling group, the number of predictor variables in each model (K), AICc scores (AICc), change in AICc score from the top ranked model (ΔAICc), model AICc weight (AICcWt), cumulative weights from the top ranked model descending to the lowest ranked model (Cum.Wt), and log likelihood (LL). Estimates were made from the selected final models in bold.

Bird Group	Model Group	K	AICc	ΔAICc	AICcWt	Cum.Wt	LL
Any Duck	**No management**	**5**	**200.47**	**0**	**0**	**1**	**-95.07**
	Management	9	211.2	10.73	0	1	-96.11
	NULL	1	239.65	39.18	0	1	-118.81
Blue-winged Teal	**No management**	**5**	**221.76**	**0**	**0.90**	**0.90**	**-105.72**
	Management	9	226.18	4.42	0.10	1	-103.60
	NULL	1	258.01	36.25	0	1	-128.00
Gadwall	**No management**	**4**	**221.95**	**0**	**0.60**	**0.60**	**-106.87**
	Management	7	222.77	0.83	0.40	0.99	-104.08
	NULL	1	230.83	8.88	0.01	1	-114.40
Mallard	**No management**	**4**	**249.89**	**0**	**0.98**	**0.98**	**-120.84**
	Management	6	258.05	8.16	0.02	1	-122.80
	NULL	1	268.95	19.06	0	1	-133.46
Northern Pintail	**No management**	**5**	**161.81**	**0**	**0.87**	**0.87**	**-75.74**
	Management	9	165.68	3.87	0.13	1	-73.35
	NULL	1	175.4	13.59	0	1	-86.69
Northern Shoveler	**No management**	**4**	**182.9**	**0**	**0.84**	**0.84**	**-87.35**
	Management	8	186.15	3.25	0.16	1	-84.69
	NULL	1	201.65	18.74	0	1	-99.81

Table A.9. Best fit occurrence model results for any duck, blue-winged teal (BWTE), gadwall (GADW), mallard (MALL), northern pintail (NOPI), and northern shoveler (NSHO) during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence intervals.

Group	Variable	$\hat{\beta}$	SE	LCL	UCL
Any Duck	Intercept	1.337	0.494	0.647	2.075
	date	0.487	0.188	0.220	0.763
	inundated area veg coverage	0.044	0.023	0.011	0.078
	inundated area veg coverage^2	-0.001	0.000	-0.001	-0.000
	inundated area	1.027	0.221	0.721	1.359
BWTE	Intercept	-2.272	0.495	-3.010	-1.580
	date	0.438	0.166	0.202	0.681
	depth	7.720	2.478	4.170	11.341
	depth^2	-4.562	2.552	-8.200	-0.729
	inundated area	0.556	0.197	0.278	0.848
GADW	Intercept	-0.903	0.426	-1.532	-0.302
	inundated area veg coverage	-0.006	0.021	-0.037	0.025
	inundated area veg coverage^2	-0.000	0.000	-0.001	0.000
	inundated area veg height	2.614	0.966	1.240	4.037
MALL	Intercept	-0.116	0.410	-0.711	0.475
	inundated area veg coverage	0.042	0.020	0.014	0.072
	inundated area veg coverage^2	-0.001	0.000	-0.001	-0.000
	inundated area	0.693	0.181	0.440	0.961
NOPI	Intercept	-3.837	0.809	-5.102	-2.758
	depth^2	-9.924	4.785	-17.981	-4.061
	depth	10.887	4.161	5.418	17.507
	inundated area	0.830	0.256	0.470	1.211
	proportion inundated	0.582	0.263	0.193	0.962
NSHO	Intercept	-1.481	0.533	-2.289	-0.746
	inundated area	0.977	0.238	0.648	1.335
	inundated area veg coverage	0.029	0.026	-0.008	0.067
	inundated area veg coverage^2	-0.000	0.000	-0.001	-0.000

Table A.10. Candidate duck density models resulting from the variable selection process for each model group. Bird groups are separated by a light gray highlighted row. Bird groups which used a Poisson distribution instead of a negative binomial distribution are indicated. These data include the modeling group, the number of predictor variables in each model (K), AIC_C scores (AIC_C), change in AIC_C score from the top ranked model (ΔAIC_C), model AIC_C weight (AIC_CWt), cumulative weights from the top ranked model descending to the lowest ranked model (Cum.Wt), and log likelihood (LL). Estimates were made from the selected final models in bold.

Bird Group	Model Group	K	AICc	ΔAICc	AICcWt	Cum.Wt	LL
Any Duck	**No management**	**12**	**986.02**	**0**	**0.81**	**0.81**	**-480.14**
	Management	16	988.89	2.87	0.19	1	-476.90
	NULL	7	1026.54	40.53	0	1	-505.97
Blue-winged Teal	**No management**	**11**	**574.22**	**0**	**0.98**	**0.98**	**-275.38**
	Management	13	582.32	8.09	0.02	1	-277.14
	NULL	7	594.87	20.65	0	1	-290.13
Gadwall - Poisson	**Management**	**11**	**407.94**	**0**	**0.99**	**0.99**	**-192.24**
	No management	8	416.74	8.8	0.01	1	-199.98
	NULL	5	436.34	28.4	0	1	-213.01
Mallard	**No management**	**9**	**638.5**	**0**	**0.95**	**0.95**	**-309.76**
	NULL	6	644.45	5.95	0.05	1	-316.00
	Management	11	648.81	10.31	0	1	-312.68
Northern Pintail	**No management**	**10**	**258.79**	**0**	**0.90**	**0.90**	**-118.79**
	NULL	7	263.25	4.46	0.10	1	-124.32
	Management	20	283.99	25.2	0	1	-119.55
Northern Shoveler - Poisson	**Management**	**10**	**344.72**	**0**	**1**	**1**	**-161.75**
	No management	10	364.13	19.41	0	1	-171.46
	NULL	5	393.86	49.15	0	1	-191.77

Table A.11. Coefficient estimates ($\hat{\beta}$) from the count portion of the best fit density model for "any duck", blue-winged teal (BWTE), gadwall (GADW), mallard (MALL), northern pintail (NOPI), and northern shoveler (NSHO). Included are the standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence intervals.

Group	Variable	$\hat{\beta}$	SE	LCL	UCL
Any Duck	Intercept	2.557	0.338	2.070	3.044
	depth^2	-3.413	1.367	-5.381	-1.444
	depth	3.070	1.333	1.152	4.989
	inundated area	-0.854	0.113	-1.017	-0.690
	inundated area veg coverage	-0.398	1.215	-2.147	1.351
	inundated area veg coverage^2	-1.058	1.269	-2.885	0.769
BWTE	Intercept	2.441	0.252	2.078	2.804
	inundated area veg coverage	0.437	1.301	-1.437	2.310
	inundated area veg coverage^2	-1.490	1.375	-3.468	0.489
	date	-0.392	0.092	-0.524	-0.260
	inundated area	-0.998	0.132	-1.187	-0.808
GADW	Intercept	2.035	0.133	1.844	2.226
	burned	-0.967	0.401	-1.545	-0.390
	disked	-0.334	0.211	-0.638	-0.030
	harvested	0.326	0.253	-0.039	0.691
	mowed	-1.006	0.669	-1.969	-0.043
	inundated area	-1.198	0.105	-1.349	-1.046
	date	-0.499	0.089	-0.627	-0.371
MALL	Intercept	2.222	0.267	1.838	2.606
	inundated area veg coverage	-1.954	1.344	-3.889	-0.020
	inundated area veg coverage^2	0.700	1.415	-1.336	2.737
	inundated area	-1.108	0.125	-1.287	-0.929
NOPI	Intercept	2.571	0.412	1.978	3.163
	inundated area veg coverage	-7.476	2.615	-11.240	-3.712
	inundated area veg coverage^2	6.006	2.682	2.145	9.867
	inundated area	-1.240	0.311	-1.687	-0.792
NSHO	Intercept	0.927	0.284	0.518	1.336
	burned	0.723	0.345	0.227	1.220
	disked	0.654	0.302	0.220	1.088
	harvested	2.461	0.339	1.974	2.948
	mowed	0.463	0.479	-0.227	1.153
	inundated area	-0.862	0.119	-1.033	-0.692

Table A.12. Hurdle density estimates (birds per hectare) of "any duck", gadwall (GADW), and northern shoveler (NSHO) for each management method during springs 2017–2019 within agriculturally-situated wetlands in the Drift Prairie of North Dakota and South Dakota. Included are standard errors (SE) and lower (LCL) and upper (UCL) 85% confidence limits.

Group	Management	Density	SE	LCL	UCL
GADW	idled	2.233	0.513	1.491	2.976
	burned	0.900	0.242	0.551	1.250
	disked	1.606	0.382	1.053	2.158
	harvested	3.092	0.890	1.806	4.378
	mowed	0.872	0.321	0.408	1.336
NSHO	idled	0.653	0.171	0.405	0.901
	burned	1.233	0.394	0.664	1.802
	disked	1.154	0.314	0.701	1.607
	harvested	6.962	2.086	3.947	9.976
	mowed	0.965	0.350	0.458	1.472

APPENDIX B. CHAPTER 3 SUPPLEMENTAL TABLES

Table B.1. Coefficient estimates from the final reduced model for planted acres of corn. Intercept included landform_upland, owner_A, and year_2004. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence limits. Bolded text rows indicate the 85% confidence limits did not include '0'.

Variable	$\hat{\beta}$	SE	p.value	LCL	UCL
(Intercept)	**11.340**	**0.214**	**0.000**	**11.030**	**11.663**
landform_dist30	**-2.443**	**0.129**	**0.000**	**-2.629**	**-2.256**
landform_dist20	**-2.838**	**0.129**	**0.000**	**-3.025**	**-2.652**
landform_dist10	**-3.482**	**0.128**	**0.000**	**-3.668**	**-3.297**
landform_sink1	**-3.191**	**0.128**	**0.000**	**-3.377**	**-3.006**
landform_sink2	**-5.109**	**0.129**	**0.000**	**-5.297**	**-4.920**
landform_sink3	**-4.383**	**0.131**	**0.000**	**-4.575**	**-4.191**
landform_temp	**-3.883**	**0.131**	**0.000**	**-4.074**	**-3.690**
landform_seasonal	**-3.794**	**0.131**	**0.000**	**-3.988**	**-3.600**
farmer_C	**0.212**	**0.098**	**0.031**	**0.070**	**0.355**
farmer_D	**0.832**	**0.099**	**0.000**	**0.678**	**0.987**
year_2005	-0.234	0.269	0.386	-0.618	0.161
year_2006	**-1.404**	**0.269**	**0.000**	**-1.790**	**-1.007**
year_2007	**-1.047**	**0.269**	**0.000**	**-1.433**	**-0.651**
year_2008	-0.075	0.232	0.747	-0.411	0.259
year_2009	**-1.357**	**0.254**	**0.000**	**-1.725**	**-0.983**
year_2010	**-1.474**	**0.253**	**0.000**	**-1.840**	**-1.103**
year_2011	**-1.286**	**0.272**	**0.000**	**-1.677**	**-0.884**
year_2012	**-0.540**	**0.241**	**0.025**	**-0.889**	**-0.191**
year_2013	-0.345	0.254	0.175	-0.711	0.025
year_2014	**-0.372**	**0.207**	**0.072**	**-0.671**	**-0.085**
year_2015	0.105	0.242	0.664	-0.244	0.455
year_2016	-0.125	0.204	0.541	-0.424	0.162
year_2017	0.108	0.203	0.594	-0.204	0.410
year_2018	-0.154	0.202	0.447	-0.458	0.139
year_2019	-0.051	0.221	0.816	-0.382	0.269
year_2020	**-0.467**	**0.220**	**0.034**	**-0.795**	**-0.148**
year_2021	**0.508**	**0.258**	**0.049**	**0.128**	**0.885**

Table B.2. Coefficient estimates from the final reduced model for planted acres of soybeans. Intercept included landform_upland, owner_A, and year_2003. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence limits. Bolded text rows indicate the 85% confidence limits did not include '0'.

Variable	$\hat{\boldsymbol{\beta}}$	SE	p.value	LCL	UCL
(Intercept)	**10.433**	**0.446**	**0.000**	**9.842**	**11.143**
landform_dist30	**-2.371**	**0.122**	**0.000**	**-2.548**	**-2.194**
landform_dist20	**-2.774**	**0.122**	**0.000**	**-2.951**	**-2.597**
landform_dist10	**-3.419**	**0.122**	**0.000**	**-3.595**	**-3.243**
landform_sink1	**-3.222**	**0.122**	**0.000**	**-3.399**	**-3.046**
landform_sink2	**-5.086**	**0.123**	**0.000**	**-5.265**	**-4.908**
landform_sink3	**-4.283**	**0.125**	**0.000**	**-4.466**	**-4.099**
landform_temp	**-3.808**	**0.124**	**0.000**	**-3.991**	**-3.626**
landform_seasonal	**-3.963**	**0.124**	**0.000**	**-4.146**	**-3.780**
farmer_C	0.097	0.099	0.325	-0.048	0.244
farmer_D	**0.397**	**0.088**	**0.000**	**0.260**	**0.534**
year_2004	**1.696**	**0.480**	**0.000**	**0.947**	**2.348**
year_2005	**1.017**	**0.464**	**0.028**	**0.288**	**1.640**
year_2006	0.576	0.464	0.214	-0.153	1.199
year_2007	-0.080	0.471	0.865	-0.817	0.554
year_2008	**1.130**	**0.465**	**0.015**	**0.400**	**1.754**
year_2009	0.001	0.471	0.998	-0.736	0.636
year_2010	0.498	0.460	0.279	-0.227	1.112
year_2011	0.309	0.448	0.490	-0.403	0.902
year_2012	**0.859**	**0.446**	**0.054**	**0.150**	**1.450**
year_2013	**0.843**	**0.450**	**0.061**	**0.131**	**1.437**
year_2014	**1.070**	**0.458**	**0.019**	**0.348**	**1.680**
year_2015	**0.822**	**0.456**	**0.071**	**0.102**	**1.430**
year_2016	**1.288**	**0.444**	**0.004**	**0.582**	**1.874**
year_2017	**1.240**	**0.442**	**0.005**	**0.532**	**1.829**
year_2018	**0.935**	**0.448**	**0.037**	**0.221**	**1.533**
year_2019	0.271	0.448	0.544	-0.440	0.864
year_2020	0.609	0.450	0.175	-0.104	1.206
year_2021	**0.797**	**0.468**	**0.089**	**0.061**	**1.426**

Table B.3. Coefficient estimates from the final reduced model for proportion of each landform planted for corn. Intercept included landform_sink1, owner_A, and year_2004. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence limits. Bolded text rows indicate the 85% confidence limits did not include '0'.

Variable	$\hat{\beta}$	SE	p.value	LCL	UCL
(Intercept)	**2.824**	**0.530**	**0.000**	**2.084**	**3.619**
landform_sink2	**-0.378**	**0.232**	**0.104**	**-0.714**	**-0.044**
landform_sink3	**-1.001**	**0.236**	**0.000**	**-1.342**	**-0.664**
landform_temp	**-0.415**	**0.236**	**0.078**	**-0.755**	**-0.076**
landform_seasonal	**-1.412**	**0.239**	**0.000**	**-1.759**	**-1.071**
farmer_C	-0.278	0.224	0.213	-0.600	0.044
farmer_D	**-0.870**	**0.228**	**0.000**	**-1.200**	**-0.543**
year_2005	**-1.504**	**0.644**	**0.020**	**-2.457**	**-0.593**
year_2006	**-3.548**	**0.863**	**0.000**	**-4.931**	**-2.400**
year_2007	**-2.554**	**0.701**	**0.000**	**-3.612**	**-1.583**
year_2008	**-0.881**	**0.572**	**0.124**	**-1.728**	**-0.071**
year_2009	**-3.932**	**0.905**	**0.000**	**-5.414**	**-2.745**
year_2010	**-3.631**	**0.816**	**0.000**	**-4.922**	**-2.539**
year_2011	**-4.098**	**1.048**	**0.000**	**-5.902**	**-2.763**
year_2012	**-2.125**	**0.603**	**0.000**	**-3.025**	**-1.282**
year_2013	**-1.445**	**0.616**	**0.019**	**-2.356**	**-0.575**
year_2014	**-1.875**	**0.523**	**0.000**	**-2.659**	**-1.146**
year_2015	-0.321	0.617	0.602	-1.222	0.565
year_2016	**-1.139**	**0.518**	**0.028**	**-1.916**	**-0.415**
year_2017	**-1.378**	**0.515**	**0.007**	**-2.151**	**-0.659**
year_2018	**-1.500**	**0.512**	**0.003**	**-2.268**	**-0.786**
year_2019	**-2.166**	**0.553**	**0.000**	**-2.989**	**-1.390**
year_2020	**-2.129**	**0.549**	**0.000**	**-2.948**	**-1.359**
year_2021	-0.485	0.671	0.470	-1.459	0.483

Table B.4. Coefficient estimates from the final reduced model for proportion of each landform planted for soybeans. Intercept included landform_sink1, owner_A, and year_2003. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence limits. Bolded text rows indicate the 85% confidence limits did not include '0'.

Variable	$\hat{\beta}$	SE	p.value	LCL	UCL
(Intercept)	**1.491**	**0.967**	**0.123**	**0.014**	**2.880**
landform_sink2	**-0.466**	**0.211**	**0.027**	**-0.771**	**-0.163**
landform_sink3	**-1.089**	**0.218**	**0.000**	**-1.405**	**-0.777**
landform_temp	**-0.424**	**0.214**	**0.047**	**-0.733**	**-0.117**
landform_seasonal	**-1.408**	**0.221**	**0.000**	**-1.729**	**-1.092**
farmer_C	-0.267	0.218	0.221	-0.582	0.047
farmer_D	**-1.186**	**0.202**	**0.000**	**-1.480**	**-0.897**
year_2004	0.973	1.051	0.354	-0.529	2.561
year_2005	0.440	1.008	0.662	-1.005	1.970
year_2006	-0.981	1.038	0.345	-2.478	0.581
year_2007	**-2.034**	**1.170**	**0.082**	**-3.773**	**-0.328**
year_2008	1.159	1.020	0.256	-0.301	2.706
year_2009	**-2.248**	**1.209**	**0.063**	**-4.071**	**-0.503**
year_2010	-0.521	1.011	0.607	-1.973	1.010
year_2011	-1.080	0.982	0.272	-2.490	0.416
year_2012	0.029	0.974	0.977	-1.368	1.515
year_2013	-0.369	0.982	0.707	-1.777	1.127
year_2014	-0.443	1.002	0.659	-1.881	1.078
year_2015	-1.044	1.016	0.304	-2.506	0.492
year_2016	0.620	0.973	0.524	-0.775	2.106
year_2017	-0.134	0.964	0.889	-1.517	1.340
year_2018	-0.226	0.979	0.817	-1.631	1.267
year_2019	-0.971	0.976	0.320	-2.372	0.518
year_2020	-1.054	0.982	0.283	-2.463	0.441
year_2021	1.004	1.048	0.338	-0.495	2.588

Table B.5. Coefficient estimates from the final reduced model for corn yield. Intercept included landform_upland, owner_A, and year_2003. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence limits. Bolded text rows indicate the 85% confidence limits did not include ‘0’.

Variable	$\hat{\beta}$	SE	p.value	LCL	UCL
(Intercept)	**137.692**	**6.532**	**0.000**	**128.285**	**147.099**
landform_dist30	**-10.875**	**3.223**	**0.001**	**-15.517**	**-6.233**
landform_dist20	**-14.731**	**3.223**	**0.000**	**-19.373**	**-10.089**
landform_dist10	**-19.615**	**3.209**	**0.000**	**-24.236**	**-14.994**
landform_sink1	**-13.051**	**3.195**	**0.000**	**-17.652**	**-8.450**
landform_sink2	**-20.850**	**3.246**	**0.000**	**-25.525**	**-16.175**
landform_sink3	**-18.464**	**3.493**	**0.000**	**-23.495**	**-13.433**
landform_temp	**-19.827**	**3.311**	**0.000**	**-24.596**	**-15.058**
landform_seasonal	**-38.387**	**3.331**	**0.000**	**-43.184**	**-33.591**
farmer_B	-8.075	6.159	0.190	-16.945	0.795
farmer_C	**-21.908**	**2.648**	**0.000**	**-25.722**	**-18.094**
farmer_D	**-6.871**	**2.227**	**0.002**	**-10.078**	**-3.664**
year_2004	1.242	7.444	0.868	-9.478	11.962
year_2005	8.751	8.274	0.290	-3.164	20.666
year_2006	**21.661**	**7.816**	**0.006**	**10.405**	**32.916**
year_2007	2.924	8.339	0.726	-9.085	14.933
year_2008	**21.481**	**7.228**	**0.003**	**11.072**	**31.890**
year_2009	**66.377**	**7.596**	**0.000**	**55.438**	**77.316**
year_2010	**47.742**	**7.609**	**0.000**	**36.785**	**58.700**
year_2011	**-16.431**	**6.854**	**0.017**	**-26.301**	**-6.561**
year_2012	**40.650**	**6.622**	**0.000**	**31.114**	**50.186**
year_2013	**30.798**	**6.846**	**0.000**	**20.939**	**40.657**
year_2014	**32.176**	**6.550**	**0.000**	**22.744**	**41.609**
year_2015	9.242	7.472	0.216	-1.518	20.002
year_2016	**60.751**	**6.470**	**0.000**	**51.434**	**70.068**
year_2017	**45.183**	**6.440**	**0.000**	**35.909**	**54.458**
year_2018	**78.234**	**6.384**	**0.000**	**69.041**	**87.428**
year_2019	**33.538**	**6.802**	**0.000**	**23.742**	**43.334**
year_2020	**27.270**	**6.784**	**0.000**	**17.501**	**37.040**
year_2021	**62.881**	**7.782**	**0.000**	**51.674**	**74.089**

Table B.6. Coefficient estimates from the final reduced model for soybean yield. Intercept included landform_upland, owner_A, and year_2003. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence limits. Bolded text rows indicate the 85% confidence limits did not include '0'.

Variable	$\hat{\beta}$	SE	p.value	LCL	UCL
(Intercept)	**26.738**	**1.547**	**0.000**	**24.511**	**28.965**
landform_dist30	**-2.055**	**0.757**	**0.007**	**-3.145**	**-0.964**
landform_dist20	**-2.077**	**0.757**	**0.006**	**-3.167**	**-0.986**
landform_dist10	**-2.108**	**0.755**	**0.005**	**-3.194**	**-1.021**
landform_sink1	-0.598	0.754	0.428	-1.684	0.488
landform_sink2	-0.719	0.768	0.349	-1.824	0.386
landform_sink3	-0.175	0.817	0.831	-1.351	1.001
landform_temp	0.219	0.771	0.777	-0.892	1.329
landform_seasonal	**-2.471**	**0.780**	**0.002**	**-3.593**	**-1.348**
farmer_B	**-3.814**	**1.280**	**0.003**	**-5.656**	**-1.971**
farmer_C	**-5.076**	**0.556**	**0.000**	**-5.876**	**-4.276**
farmer_D	**4.795**	**0.565**	**0.000**	**3.981**	**5.609**
year_2004	**4.348**	**1.897**	**0.022**	**1.616**	**7.081**
year_2005	**8.197**	**1.849**	**0.000**	**5.535**	**10.860**
year_2006	**13.369**	**1.789**	**0.000**	**10.793**	**15.945**
year_2007	**7.987**	**1.866**	**0.000**	**5.300**	**10.673**
year_2008	**3.568**	**1.841**	**0.053**	**0.918**	**6.219**
year_2009	**10.216**	**1.935**	**0.000**	**7.430**	**13.002**
year_2010	**14.557**	**1.785**	**0.000**	**11.986**	**17.127**
year_2011	**4.280**	**1.632**	**0.009**	**1.930**	**6.630**
year_2012	**19.743**	**1.560**	**0.000**	**17.497**	**21.989**
year_2013	**13.569**	**1.596**	**0.000**	**11.271**	**15.866**
year_2014	**15.988**	**1.657**	**0.000**	**13.601**	**18.374**
year_2015	**10.550**	**1.688**	**0.000**	**8.119**	**12.980**
year_2016	**18.174**	**1.558**	**0.000**	**15.931**	**20.418**
year_2017	**10.851**	**1.503**	**0.000**	**8.687**	**13.015**
year_2018	**19.517**	**1.521**	**0.000**	**17.327**	**21.707**
year_2019	**8.872**	**1.565**	**0.000**	**6.618**	**11.126**
year_2020	**16.956**	**1.600**	**0.000**	**14.651**	**19.260**
year_2021	**29.240**	**1.714**	**0.000**	**26.771**	**31.708**

Table B.7. Coefficient estimates from the final reduced model for corn profit. Intercept included landform_upland, owner_A, and year_2004. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence limits. Bolded text rows indicate the 85% confidence limits did not include ‘0’.

Variable	$\hat{\beta}$	SE	p.value	LCL	UCL
(Intercept)	**0.180**	**0.025**	**0.000**	**0.144**	**0.216**
landform_dist30	**-0.041**	**0.015**	**0.006**	**-0.062**	**-0.020**
landform_dist20	**-0.052**	**0.015**	**0.001**	**-0.073**	**-0.030**
landform_dist10	**-0.066**	**0.015**	**0.000**	**-0.087**	**-0.044**
landform_sink1	**-0.050**	**0.015**	**0.001**	**-0.071**	**-0.028**
landform_sink2	**-0.093**	**0.015**	**0.000**	**-0.114**	**-0.071**
landform_sink3	**-0.086**	**0.016**	**0.000**	**-0.109**	**-0.063**
landform_temp	**-0.087**	**0.015**	**0.000**	**-0.109**	**-0.065**
landform_seasonal	**-0.131**	**0.015**	**0.000**	**-0.153**	**-0.109**
farmer_C	0.002	0.011	0.868	-0.015	0.018
farmer_D	**-0.062**	**0.012**	**0.000**	**-0.079**	**-0.046**
year_2005	-0.031	0.032	0.328	-0.076	0.015
year_2006	0.034	0.032	0.285	-0.012	0.079
year_2007	0.033	0.032	0.298	-0.013	0.078
year_2008	**0.146**	**0.027**	**0.000**	**0.108**	**0.185**
year_2009	**0.238**	**0.030**	**0.000**	**0.195**	**0.282**
year_2010	**0.304**	**0.030**	**0.000**	**0.261**	**0.346**
year_2011	**0.256**	**0.033**	**0.000**	**0.209**	**0.303**
year_2012	**0.356**	**0.028**	**0.000**	**0.316**	**0.396**
year_2013	**0.325**	**0.029**	**0.000**	**0.283**	**0.367**
year_2014	**0.161**	**0.024**	**0.000**	**0.126**	**0.195**
year_2015	-0.010	0.028	0.717	-0.050	0.030
year_2016	**0.211**	**0.024**	**0.000**	**0.177**	**0.245**
year_2017	**0.140**	**0.023**	**0.000**	**0.106**	**0.174**
year_2018	**0.230**	**0.023**	**0.000**	**0.197**	**0.264**
year_2019	**0.087**	**0.026**	**0.001**	**0.050**	**0.124**
year_2020	**0.077**	**0.026**	**0.003**	**0.040**	**0.114**
year_2021	**0.153**	**0.030**	**0.000**	**0.110**	**0.196**

Table B.8. Coefficient estimates from the final reduced model for soybean profit. Intercept included landform_upland, owner_A, and year_2003. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence limits. Bolded text rows indicate the 85% confidence limits did not include ‘0’.

Variable	$\hat{\beta}$	SE	p.value	LCL	UCL
(Intercept)	**0.062**	**0.034**	**0.073**	**0.012**	**0.111**
landform_dist30	**-0.022**	**0.009**	**0.022**	**-0.035**	**-0.008**
landform_dist20	**-0.024**	**0.009**	**0.011**	**-0.037**	**-0.010**
landform_dist10	**-0.024**	**0.009**	**0.009**	**-0.038**	**-0.011**
landform_sink1	**-0.020**	**0.009**	**0.031**	**-0.034**	**-0.007**
landform_sink2	**-0.040**	**0.009**	**0.000**	**-0.054**	**-0.026**
landform_sink3	**-0.042**	**0.010**	**0.000**	**-0.057**	**-0.028**
landform_temp	**-0.022**	**0.010**	**0.024**	**-0.036**	**-0.008**
landform_seasonal	**-0.050**	**0.010**	**0.000**	**-0.064**	**-0.036**
farmer_C	**-0.019**	**0.008**	**0.012**	**-0.030**	**-0.008**
farmer_D	0.010	0.007	0.155	-0.000	0.020
year_2004	0.039	0.037	0.290	-0.014	0.092
year_2005	-0.001	0.036	0.967	-0.053	0.050
year_2006	**0.098**	**0.036**	**0.006**	**0.047**	**0.150**
year_2007	**0.063**	**0.036**	**0.086**	**0.010**	**0.115**
year_2008	**0.089**	**0.036**	**0.013**	**0.037**	**0.140**
year_2009	**0.149**	**0.036**	**0.000**	**0.097**	**0.201**
year_2010	**0.206**	**0.035**	**0.000**	**0.155**	**0.257**
year_2011	**0.172**	**0.035**	**0.000**	**0.122**	**0.222**
year_2012	**0.329**	**0.034**	**0.000**	**0.280**	**0.379**
year_2013	**0.286**	**0.035**	**0.000**	**0.236**	**0.336**
year_2014	**0.253**	**0.035**	**0.000**	**0.202**	**0.304**
year_2015	**0.186**	**0.035**	**0.000**	**0.135**	**0.236**
year_2016	**0.174**	**0.034**	**0.000**	**0.125**	**0.223**
year_2017	**0.165**	**0.034**	**0.000**	**0.116**	**0.214**
year_2018	**0.259**	**0.035**	**0.000**	**0.209**	**0.309**
year_2019	**0.107**	**0.034**	**0.002**	**0.057**	**0.156**
year_2020	**0.188**	**0.035**	**0.000**	**0.138**	**0.238**
year_2021	**0.268**	**0.036**	**0.000**	**0.216**	**0.320**

APPENDIX C. CHAPTER 4 SUPPLEMENTAL TABLES

Table C.1. Model selection table for each land scenario and model group for corn profit and yield models. Drop variable was the variable removed from the model during the variable selection process. Also included are the conditional log likelihood (cll), degrees of freedom (df), number of parameters (K), and the difference in cAIC between each model and the full or reduced interaction models (cAIC diff).

Corn							
Land Scenario	Model Group	Drop Term	cll	df	cAIC	K	cAIC diff
Known Farmed Land	Profit Interaction	UPI	843.6	97	-1494.1	48	-10.2
		USCV	843.4	97	-1493.6	48	-9.8
		winter SPEI	842.6	97	-1492.1	48	-8.2
		late SPEI	839.9	97	-1486.8	48	-2.9
		Full	846.5	105	-1483.9	56	0.0
		early SPEI	809.7	96	-1426.9	48	57.0
	Profit Main Effects	late SPEI	828.6	72	-1514.2	23	-1.3
		UPI	828.9	72	-1513.1	23	-0.1
		USCV	828.7	72	-1513.0	23	-0.1
		Reduced Inter.	829.0	73	-1512.9	24	0.0
		winter SPEI	820.9	71	-1498.8	23	14.1
	Yield Interactions	UPI	-9517.8	101	19238.6	48	-7.2
		Full	-9513.4	110	19245.8	56	0.0
		late SPEI	-9522.4	101	19247.7	48	1.8
		winter SPEI	-9524.5	101	19251.9	48	6.0
		USCV	-9536.1	101	19275.1	48	29.3
		early SPEI	-9552.7	101	19308.0	48	62.2
	Yield Main Effects	UPI	-9527.0	93	19240.5	39	-0.1
		Reduced Inter.	-9526.9	93	19240.6	40	0.0
		late SPEI	-9555.7	93	19296.5	39	55.9
All Farmable Land	Profit Interaction	late SPEI	1409.8	99	-2621.7	48	-5.6
		Full	1415.0	107	-2616.1	56	0.0
		USCV	1407.0	99	-2615.9	48	0.1
		UPI	1404.9	99	-2611.9	48	4.2
		winter SPEI	1399.4	99	-2601.0	48	15.1
		early SPEI	1380.9	99	-2564.0	48	52.1
	Profit Main Effects	Reduced Inter.	1401.9	91	-2621.7	40	0.0
		USCV	1401.3	91	-2621.3	39	0.4
		late SPEI	1400.6	90	-2621.1	39	0.6
	Yield Interactions	late SPEI	-10427.4	102	21058.6	48	-0.9
		Full	-10419.9	110	21059.6	56	0.0
		UPI	-10432.0	102	21067.8	48	8.2
		USCV	-10432.8	102	21069.5	48	10.0
		winter SPEI	-10443.2	102	21090.0	48	30.5
		early SPEI	-10444.3	102	21092.4	48	32.9
	Yield Main Effects	Reduced Inter.	-10427.4	102	21058.6	48	0.0
		late SPEI	-10463.7	101	21129.7	47	71.1

Table C.2. Model selection table for each land scenario and model group for soybean profit and yield models. Drop variable was the variable removed from the model during the variable selection process. Also included are the conditional log likelihood (cll), degrees of freedom (df), number of parameters (K), and the difference in cAIC between each model and the full or reduced interaction models (cAIC diff).

Soybeans							
Land Scenario	**Model Group**	**Drop Term**	**cll**	**df**	**cAIC**	**K**	**cAIC diff**
Known Farmed Land	Profit Interaction	winter SPEI	1650.08	97	-3106.4	48	-11.3
		late SPEI	1649.41	97	-3105.1	48	-10.0
		UPI	1645.07	97	-3096.4	48	-1.3
		Full	1652.42	105	-3095.1	56	0.0
		USCV	1638.14	97	-3082.7	48	12.4
		early SPEI	1618.07	97	-3042.9	48	52.2
	Profit Main Effects	winter SPEI	1638.01	80	-3116.2	31	-1.5
		Reduced Inter.	1638.17	81	-3114.7	32	0.0
		UPI	1637.9	81	-3114.4	31	0.3
		late SPEI	1546.76	79	-2935.8	31	178.9
	Yield Interactions	late SPEI	-8610.48	105	17431.8	48	-8.0
		UPI	-8612.75	105	17436.3	48	-3.5
		Full	-8606.45	113	17439.8	56	0.0
		winter SPEI	-8614.86	105	17440.5	48	0.7
		USCV	-8619.53	105	17449.8	48	10.0
		early SPEI	-8623.56	105	17457.9	48	18.1
	Yield Main Effects	UPI	-8627.2	89	17432.9	31	-0.2
		Reduced Inter.	-8627.15	89	17433.1	32	0.0
		winter SPEI	-8640.48	89	17458.3	31	25.2
		late SPEI	-8643.51	88	17463.7	31	30.6
All Farmable Land	Profit Interaction	late SPEI	2008.54	99	-3819.4	48	-7.3
		UPI	2007.49	99	-3817.2	48	-5.2
		USCV	2005.17	99	-3812.6	48	-0.6
		Full	2012.88	107	-3812.0	56	0.0
		winter SPEI	1992.91	99	-3788.2	48	23.8
		early SPEI	1978.2	99	-3758.9	48	53.1
	Profit Main Effects	Reduced Inter.	1992.63	83	-3819.5	32	0.0
		UPI	1992.41	83	-3819.3	31	0.2
		USCV	1991.73	83	-3818.2	31	1.4
		late SPEI	1956.15	81	-3749.4	31	70.2
	Yield Interactions	late SPEI	-9362.15	106	18936.5	48	-10.3
		UPI	-9367.3	106	18946.7	48	0.0
		Full	-9359.3	114	18946.7	56	0.0
		USCV	-9368.96	106	18950.0	48	3.3
		winter SPEI	-9391.5	106	18994.9	48	48.2
		early SPEI	-9407.7	106	19027.2	48	80.4
	Yield Main Effects	late SPEI	-9369.67	97	18933.5	39	-2.1
		UPI	-9369.68	98	18935.3	39	-0.3
		Reduced Inter.	-9369.72	98	18935.6	40	0.0

Table C.3. Final, full, and null models for each land scenario and response variable for corn and soybeans. These data also include conditional log likelihood (cll), degrees of freedom (df), conditional AIC (cAIC), number of parameters (K), change in cAIC from the top ranked model (ΔcAIC), and the model cAIC weight (cAIC wt). Estimates were made from the final selected models.

Corn

Land Scenario	Response	Model	cll	df	cAIC	K	ΔcAIC	cAIC wt
Known Farmed Land	Profit	Final	828.2	71	-1514.5	21	0.0	1.0
		Full	846.5	105	-1483.9	56	30.6	0.0
		Null	762.0	60	-1403.9	11	110.6	0.0
	Yield	Final	-9527.0	93	19240.5	39	0.0	0.9
		Full	-9513.4	110	19245.8	56	5.3	0.1
		Null	-9720.5	66	19572.0	11	331.5	0.0
All Farmable Land	Profit	Final	1400.1	90	-2620.6	38	0.0	0.9
		Full	1415.0	107	-2616.1	56	4.6	0.1
		Null	1280.2	63	-2434.7	11	185.9	0.0
	Yield	Final	-10427.4	102	21058.6	48	0.0	0.6
		Full	-10419.9	110	21059.6	56	0.9	0.4
		Null	-10633.7	66	21399.7	11	341.0	0.0

Soybeans

Land Scenario	Response	Model	cll	df	cAIC	K	ΔcAIC	cAIC wt
Known Farmed Land	Profit	Final	1637.7	80	-3115.9	30	0.0	1.0
		Full	1652.4	105	-3095.1	56	20.8	0.0
		Null	1500.0	61	-2879.0	11	237.0	0.0
	Yield	Final	-8627.2	89	17432.9	31	0.0	1.0
		Full	-8606.5	113	17439.8	56	6.9	0.0
		Null	-8689.0	70	17517.9	11	85.0	0.0
All Farmable Land	Profit	Final	1991.7	83	-3818.3	30	0.0	1.0
		Full	2012.9	107	-3812.0	56	6.2	0.0
		Null	1875.2	63	-3624.5	11	193.7	0.0
	Yield	Final	-9369.6	97	18933.2	38	0.0	1.0
		Full	-9359.3	114	18946.7	56	13.5	0.0
		Null	-9524.4	71	19189.8	11	256.6	0.0

Table C.4. Coefficient estimates from the final reduced model for corn profit from the known farmed land scenario. Intercept included landform_upland. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence intervals. Bolded text rows indicate the 85% confidence limits did not include '0'.

Variable	$\hat{\beta}$	**SE**	**p.value**	**LCL**	**UCL**
(Intercept)	**0.320**	**0.017**	**0.000**	**0.296**	**0.345**
landform_seasonal	**-0.140**	**0.016**	**0.000**	**-0.163**	**-0.117**
landform_dist10	**-0.069**	**0.015**	**0.000**	**-0.091**	**-0.046**
landform_dist20	**-0.051**	**0.015**	**0.001**	**-0.073**	**-0.029**
landform_dist30	**-0.039**	**0.015**	**0.012**	**-0.061**	**-0.017**
landform_sink1	**-0.058**	**0.015**	**0.000**	**-0.080**	**-0.036**
landform_sink2	**-0.107**	**0.016**	**0.000**	**-0.129**	**-0.084**
landform_sink3	**-0.104**	**0.017**	**0.000**	**-0.128**	**-0.080**
landform_temp	**-0.099**	**0.016**	**0.000**	**-0.122**	**-0.076**
early SPEI	0.005	0.011	0.658	-0.011	0.022
winter SPEI	**-0.015**	**0.004**	**0.000**	**-0.020**	**-0.009**
landform_seasonal : early SPEI	**-0.058**	**0.016**	**0.000**	**-0.082**	**-0.034**
landform_dist10 : early SPEI	**-0.025**	**0.016**	**0.126**	**-0.048**	**-0.001**
landform_dist20 : early SPEI	-0.015	0.016	0.351	-0.038	0.008
landform_dist30 : early SPEI	-0.007	0.016	0.661	-0.030	0.016
landform_sink1 : early SPEI	**-0.048**	**0.016**	**0.003**	**-0.071**	**-0.025**
landform_sink2 : early SPEI	**-0.078**	**0.016**	**0.000**	**-0.102**	**-0.055**
landform_sink3 : early SPEI	**-0.084**	**0.017**	**0.000**	**-0.109**	**-0.059**
landform_temp : early SPEI	**-0.071**	**0.017**	**0.000**	**-0.095**	**-0.047**

Table C.5. Coefficient estimates from the final reduced model for corn profit from the all farmable land scenario. Intercept included landform_upland. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence intervals. Bolded text rows indicate the 85% confidence limits did not include ‘0’.

Variable	$\hat{\beta}$	SE	p.value	LCL	UCL
(Intercept)	0.094	0.170	0.583	-0.153	0.340
landform_seasonal	0.054	0.142	0.705	-0.151	0.258
landform_dist10	0.076	0.134	0.572	-0.117	0.268
landform_dist20	0.028	0.134	0.832	-0.165	0.222
landform_dist30	-0.074	0.134	0.584	-0.267	0.120
landform_sink1	0.118	0.134	0.379	-0.075	0.310
landform_sink2	**0.294**	**0.139**	**0.035**	**0.093**	**0.494**
landform_sink3	**0.247**	**0.140**	**0.078**	**0.046**	**0.448**
landform_temp	-0.156	0.137	0.254	-0.353	0.041
early SPEI	**0.018**	**0.008**	**0.038**	**0.005**	**0.030**
winter SPEI	-0.006	0.007	0.409	-0.016	0.004
UPI	0.273	0.226	0.230	-0.055	0.601
landform_seasonal : early SPEI	**-0.050**	**0.012**	**0.000**	**-0.068**	**-0.033**
landform_dist10 : early SPEI	**-0.029**	**0.012**	**0.014**	**-0.046**	**-0.012**
landform_dist20 : early SPEI	**-0.018**	**0.012**	**0.124**	**-0.035**	**-0.001**
landform_dist30 : early SPEI	-0.012	0.012	0.326	-0.029	0.005
landform_sink1 : early SPEI	**-0.046**	**0.012**	**0.000**	**-0.063**	**-0.029**
landform_sink2 : early SPEI	**-0.064**	**0.012**	**0.000**	**-0.081**	**-0.047**
landform_sink3 : early SPEI	**-0.043**	**0.012**	**0.000**	**-0.061**	**-0.026**
landform_temp : early SPEI	**-0.070**	**0.012**	**0.000**	**-0.087**	**-0.052**
landform_seasonal : winter SPEI	**-0.029**	**0.010**	**0.004**	**-0.043**	**-0.015**
landform_dist10 : winter SPEI	**-0.018**	**0.010**	**0.064**	**-0.032**	**-0.004**
landform_dist20 : winter SPEI	**-0.014**	**0.010**	**0.142**	**-0.028**	**-0.000**
landform_dist30 : winter SPEI	-0.011	0.010	0.273	-0.025	0.003
landform_sink1 : winter SPEI	**-0.029**	**0.010**	**0.002**	**-0.043**	**-0.015**
landform_sink2 : winter SPEI	**-0.048**	**0.010**	**0.000**	**-0.063**	**-0.034**
landform_sink3 : winter SPEI	**-0.036**	**0.010**	**0.000**	**-0.050**	**-0.021**
landform_temp : winter SPEI	**-0.033**	**0.010**	**0.001**	**-0.047**	**-0.019**
landform_seasonal : UPI	**-0.324**	**0.186**	**0.081**	**-0.592**	**-0.057**
landform_dist10 : UPI	-0.223	0.175	0.203	-0.475	0.029
landform_dist20 : UPI	-0.118	0.176	0.503	-0.371	0.135
landform_dist30 : UPI	0.046	0.176	0.794	-0.207	0.299
landform_sink1 : UPI	**-0.270**	**0.175**	**0.124**	**-0.522**	**-0.018**
landform_sink2 : UPI	**-0.556**	**0.183**	**0.002**	**-0.820**	**-0.293**
landform_sink3 : UPI	**-0.538**	**0.184**	**0.003**	**-0.803**	**-0.274**
landform_temp : UPI	0.013	0.179	0.941	-0.245	0.271

Table C.6. Coefficient estimates from the final reduced model for corn yield from the known farmed land scenario. Intercept included landform_upland. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence intervals. Bolded text rows indicate the 85% confidence limits did not include '0'.

Variable	$\hat{\beta}$	SE	p.value	LCL	UCL
(Intercept)	**143.808**	**20.740**	**0.000**	**113.796**	**173.819**
landform_seasonal	**-47.888**	**18.982**	**0.012**	**-75.224**	**-20.551**
landform_dist10	**-29.213**	**16.756**	**0.081**	**-53.345**	**-5.082**
landform_dist20	-18.045	17.017	0.289	-42.552	6.462
landform_dist30	-22.407	17.017	0.188	-46.914	2.099
landform_sink1	2.837	16.591	0.864	-21.057	26.731
landform_sink2	**35.148**	**16.911**	**0.038**	**10.795**	**59.502**
landform_sink3	**45.619**	**18.189**	**0.012**	**19.424**	**71.813**
landform_temp	**-34.035**	**17.638**	**0.054**	**-59.436**	**-8.633**
early SPEI	-2.364	2.366	0.318	-5.772	1.043
late SPEI	**6.405**	**0.828**	**0.000**	**5.212**	**7.597**
winter SPEI	0.094	1.975	0.962	-2.750	2.939
USCV	31.110	30.269	0.306	-12.691	74.912
landform_seasonal : early SPEI	**-14.388**	**3.425**	**0.000**	**-19.320**	**-9.456**
landform_dist10 : early SPEI	**-5.509**	**3.308**	**0.096**	**-10.272**	**-0.745**
landform_dist20 : early SPEI	-3.351	3.332	0.315	-8.149	1.447
landform_dist30 : early SPEI	-1.255	3.331	0.707	-6.052	3.543
landform_sink1 : early SPEI	**-13.274**	**3.289**	**0.000**	**-18.011**	**-8.537**
landform_sink2 : early SPEI	**-18.444**	**3.367**	**0.000**	**-23.294**	**-13.595**
landform_sink3 : early SPEI	**-16.788**	**3.649**	**0.000**	**-22.043**	**-11.532**
landform_temp : early SPEI	**-14.176**	**3.434**	**0.000**	**-19.121**	**-9.230**
landform_seasonal : winter SPEI	**-10.248**	**2.858**	**0.000**	**-14.363**	**-6.132**
landform_dist10 : winter SPEI	**-4.748**	**2.755**	**0.085**	**-8.716**	**-0.781**
landform_dist20 : winter SPEI	-3.147	2.769	0.256	-7.134	0.841
landform_dist30 : winter SPEI	-2.515	2.769	0.364	-6.503	1.472
landform_sink1 : winter SPEI	**-5.188**	**2.744**	**0.059**	**-9.139**	**-1.237**
landform_sink2 : winter SPEI	**-9.032**	**2.790**	**0.001**	**-13.050**	**-5.014**
landform_sink3 : winter SPEI	**-6.445**	**3.027**	**0.033**	**-10.804**	**-2.087**
landform_temp : winter SPEI	**-9.136**	**2.838**	**0.001**	**-13.223**	**-5.048**
landform_seasonal : USCV	21.130	28.197	0.454	-19.478	61.738
landform_dist10 : USCV	17.722	24.410	0.468	-17.432	52.875
landform_dist20 : USCV	7.733	24.692	0.754	-27.827	43.293
landform_dist30 : USCV	19.597	24.693	0.428	-15.964	55.157
landform_sink1 : USCV	-21.284	24.163	0.379	-56.081	13.513
landform_sink2 : USCV	**-78.697**	**24.731**	**0.001**	**-114.313**	**-43.080**
landform_sink3 : USCV	**-94.290**	**26.839**	**0.000**	**-132.943**	**-55.638**
landform_temp : USCV	26.339	25.631	0.304	-10.574	63.251

Table C.7. Coefficient estimates from the final reduced model for corn yield from the all farmable land scenario. Intercept included landform_upland. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence intervals. Bolded text rows indicate the 85% confidence limits did not include '0'.

Variable	$\hat{\beta}$	SE	p.value	LCL	UCL
(Intercept)	43.119	60.335	0.476	-44.396	130.633
landform_seasonal	**-77.995**	**48.444**	**0.108**	**-147.759**	**-8.231**
landform_dist10	-11.488	46.168	0.804	-77.975	54.998
landform_dist20	-6.341	46.535	0.892	-73.356	60.675
landform_dist30	-30.712	46.534	0.509	-97.726	36.302
landform_sink1	18.459	46.175	0.689	-48.039	84.956
landform_sink2	**87.727**	**47.431**	**0.065**	**19.421**	**156.032**
landform_sink3	**105.782**	**48.546**	**0.029**	**35.871**	**175.693**
landform_temp	**-154.096**	**47.440**	**0.001**	**-222.414**	**-85.777**
early SPEI	1.087	3.024	0.719	-3.268	5.442
late SPEI	**9.056**	**1.036**	**0.000**	**7.564**	**10.548**
winter SPEI	**-4.619**	**2.547**	**0.070**	**-8.287**	**-0.950**
USCV	**67.576**	**42.849**	**0.117**	**5.589**	**129.563**
UPI	81.809	84.698	0.336	-41.041	204.658
landform_seasonal : early SPEI	**-11.611**	**4.284**	**0.007**	**-17.780**	**-5.442**
landform_dist10 : early SPEI	-3.256	4.206	0.439	-9.313	2.800
landform_dist20 : early SPEI	-2.081	4.234	0.623	-8.178	4.016
landform_dist30 : early SPEI	-0.503	4.234	0.906	-6.600	5.595
landform_sink1 : early SPEI	**-12.602**	**4.203**	**0.003**	**-18.655**	**-6.549**
landform_sink2 : early SPEI	**-18.494**	**4.249**	**0.000**	**-24.613**	**-12.374**
landform_sink3 : early SPEI	**-10.169**	**4.366**	**0.020**	**-16.457**	**-3.881**
landform_temp : early SPEI	**-15.465**	**4.304**	**0.000**	**-21.663**	**-9.266**
landform_seasonal : winter SPEI	**-8.912**	**3.615**	**0.014**	**-14.117**	**-3.706**
landform_dist10 : winter SPEI	**-5.777**	**3.543**	**0.103**	**-10.879**	**-0.675**
landform_dist20 : winter SPEI	-4.254	3.565	0.233	-9.388	0.880
landform_dist30 : winter SPEI	-2.674	3.565	0.453	-7.807	2.460
landform_sink1 : winter SPEI	**-12.302**	**3.541**	**0.001**	**-17.401**	**-7.203**
landform_sink2 : winter SPEI	**-18.917**	**3.574**	**0.000**	**-24.063**	**-13.770**
landform_sink3 : winter SPEI	**-16.520**	**3.677**	**0.000**	**-21.815**	**-11.225**
landform_temp : winter SPEI	**-12.989**	**3.625**	**0.000**	**-18.210**	**-7.769**
landform_seasonal : USCV	7.994	34.201	0.815	-41.259	57.248
landform_dist10 : USCV	**60.378**	**32.647**	**0.065**	**13.363**	**107.392**
landform_dist20 : USCV	30.666	33.022	0.353	-16.889	78.221
landform_dist30 : USCV	22.935	33.022	0.487	-24.620	70.490
landform_sink1 : USCV	-19.917	32.645	0.542	-66.928	27.095
landform_sink2 : USCV	-19.282	32.652	0.555	-66.303	27.740
landform_sink3 : USCV	**-64.689**	**33.368**	**0.053**	**-112.743**	**-16.636**
landform_temp : USCV	**67.550**	**33.720**	**0.045**	**18.989**	**116.110**
landform_seasonal : UPI	-27.663	65.849	0.674	-122.492	67.166
landform_dist10 : UPI	**-91.359**	**63.230**	**0.149**	**-182.417**	**-0.301**
landform_dist20 : UPI	-49.652	63.288	0.433	-140.793	41.489
landform_dist30 : UPI	2.574	63.286	0.968	-88.565	93.712
landform_sink1 : UPI	-54.740	63.224	0.387	-145.790	36.309
landform_sink2 : UPI	**-168.150**	**64.973**	**0.010**	**-261.717**	**-74.582**
landform_sink3 : UPI	**-177.473**	**67.182**	**0.008**	**-274.221**	**-80.724**
landform_temp : UPI	67.509	63.893	0.291	-24.504	159.522

Table C.8. Coefficient estimates from the final reduced model for soybean profit from the known farmed land scenario. Intercept included landform_upland. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence intervals. Bolded text rows indicate the 85% confidence limits did not include '0'.

Variable	$\hat{\beta}$	SE	p.value	LCL	UCL
(Intercept)	**0.198**	**0.058**	**0.001**	**0.114**	**0.283**
landform_seasonal	-0.034	0.061	0.577	-0.122	0.054
landform_dist10	-0.022	0.053	0.682	-0.098	0.054
landform_dist20	-0.010	0.054	0.850	-0.087	0.067
landform_dist30	-0.036	0.054	0.503	-0.113	0.041
landform_sink1	0.034	0.053	0.517	-0.042	0.110
landform_sink2	**0.094**	**0.053**	**0.077**	**0.017**	**0.171**
landform_sink3	**0.134**	**0.056**	**0.017**	**0.053**	**0.215**
landform_temp	-0.016	0.055	0.768	-0.095	0.063
early SPEI	**0.027**	**0.007**	**0.000**	**0.016**	**0.038**
late SPEI	**-0.036**	**0.003**	**0.000**	**-0.039**	**-0.032**
USCV	0.124	0.086	0.150	-0.000	0.249
landform_seasonal : early SPEI	**-0.043**	**0.011**	**0.000**	**-0.058**	**-0.027**
landform_dist10 : early SPEI	**-0.021**	**0.010**	**0.045**	**-0.035**	**-0.006**
landform_dist20 : early SPEI	-0.012	0.010	0.238	-0.027	0.003
landform_dist30 : early SPEI	-0.006	0.010	0.537	-0.021	0.009
landform_sink1 : early SPEI	**-0.032**	**0.010**	**0.002**	**-0.047**	**-0.017**
landform_sink2 : early SPEI	**-0.051**	**0.010**	**0.000**	**-0.066**	**-0.035**
landform_sink3 : early SPEI	**-0.064**	**0.011**	**0.000**	**-0.080**	**-0.048**
landform_temp : early SPEI	**-0.042**	**0.011**	**0.000**	**-0.058**	**-0.027**
landform_seasonal : USCV	-0.032	0.092	0.730	-0.164	0.101
landform_dist10 : USCV	-0.009	0.078	0.910	-0.121	0.103
landform_dist20 : USCV	-0.021	0.079	0.786	-0.135	0.092
landform_dist30 : USCV	0.022	0.079	0.780	-0.091	0.135
landform_sink1 : USCV	-0.090	0.078	0.248	-0.202	0.022
landform_sink2 : USCV	**-0.212**	**0.078**	**0.007**	**-0.324**	**-0.099**
landform_sink3 : USCV	**-0.281**	**0.083**	**0.001**	**-0.401**	**-0.161**
landform_temp : USCV	-0.015	0.081	0.856	-0.131	0.102

Table C.9. Coefficient estimates from the final reduced model for soybean profit from the all farmable land scenario. Intercept included landform_upland. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence intervals. Bolded text rows indicate the 85% confidence limits did not include '0'.

Variable	$\hat{\beta}$	SE	p.value	LCL	UCL
(Intercept)	**0.249**	**0.012**	**0.000**	**0.232**	**0.266**
landform_seasonal	**-0.130**	**0.010**	**0.000**	**-0.144**	**-0.116**
landform_dist10	**-0.055**	**0.010**	**0.000**	**-0.069**	**-0.041**
landform_dist20	**-0.032**	**0.010**	**0.001**	**-0.046**	**-0.018**
landform_dist30	**-0.018**	**0.010**	**0.059**	**-0.032**	**-0.004**
landform_sink1	**-0.058**	**0.010**	**0.000**	**-0.072**	**-0.044**
landform_sink2	**-0.082**	**0.010**	**0.000**	**-0.096**	**-0.068**
landform_sink3	**-0.108**	**0.010**	**0.000**	**-0.122**	**-0.094**
landform_temp	**-0.081**	**0.010**	**0.000**	**-0.095**	**-0.067**
early SPEI	**0.027**	**0.006**	**0.000**	**0.018**	**0.036**
late SPEI	**-0.018**	**0.002**	**0.000**	**-0.021**	**-0.015**
winter SPEI	0.001	0.005	0.856	-0.007	0.008
landform_seasonal : early SPEI	**-0.040**	**0.009**	**0.000**	**-0.053**	**-0.026**
landform_dist10 : early SPEI	**-0.030**	**0.009**	**0.001**	**-0.043**	**-0.017**
landform_dist20 : early SPEI	**-0.017**	**0.009**	**0.057**	**-0.030**	**-0.004**
landform_dist30 : early SPEI	-0.008	0.009	0.348	-0.021	0.005
landform_sink1 : early SPEI	**-0.039**	**0.009**	**0.000**	**-0.052**	**-0.026**
landform_sink2 : early SPEI	**-0.046**	**0.009**	**0.000**	**-0.059**	**-0.033**
landform_sink3 : early SPEI	**-0.042**	**0.009**	**0.000**	**-0.055**	**-0.029**
landform_temp : early SPEI	**-0.056**	**0.009**	**0.000**	**-0.069**	**-0.043**
landform_seasonal : winter SPEI	**-0.013**	**0.007**	**0.081**	**-0.024**	**-0.002**
landform_dist10 : winter SPEI	**-0.011**	**0.007**	**0.119**	**-0.022**	**-0.001**
landform_dist20 : winter SPEI	-0.009	0.007	0.216	-0.019	0.001
landform_dist30 : winter SPEI	-0.006	0.007	0.384	-0.017	0.004
landform_sink1 : winter SPEI	**-0.018**	**0.007**	**0.012**	**-0.029**	**-0.008**
landform_sink2 : winter SPEI	**-0.031**	**0.007**	**0.000**	**-0.041**	**-0.020**
landform_sink3 : winter SPEI	**-0.030**	**0.007**	**0.000**	**-0.041**	**-0.020**
landform_temp : winter SPEI	**-0.019**	**0.007**	**0.008**	**-0.030**	**-0.009**

Table C.10. Coefficient estimates from the final reduced model for soybean yield from the known farmed land scenario. Intercept included landform_upland. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence intervals. Bolded text rows indicate the 85% confidence limits did not include '0'.

Variable	$\hat{\beta}$	SE	p.value	LCL	UCL
(Intercept)	**40.661**	**4.291**	**0.000**	**34.474**	**46.849**
landform_seasonal	-3.918	4.754	0.410	-10.764	2.928
landform_dist10	-5.244	4.189	0.211	-11.276	0.788
landform_dist20	-3.467	4.236	0.413	-9.567	2.634
landform_dist30	-4.721	4.236	0.265	-10.821	1.380
landform_sink1	1.660	4.166	0.690	-4.339	7.659
landform_sink2	**9.937**	**4.212**	**0.018**	**3.872**	**16.002**
landform_sink3	**11.214**	**4.519**	**0.013**	**4.706**	**17.722**
landform_temp	0.583	4.330	0.893	-5.652	6.818
early SPEI	**0.839**	**0.564**	**0.137**	**0.027**	**1.651**
late SPEI	**-1.121**	**0.198**	**0.000**	**-1.407**	**-0.836**
winter SPEI	**-1.057**	**0.190**	**0.000**	**-1.331**	**-0.784**
USCV	2.759	6.282	0.661	-6.297	11.816
landform_seasonal : early SPEI	**-1.733**	**0.805**	**0.031**	**-2.892**	**-0.573**
landform_dist10 : early SPEI	**-1.487**	**0.779**	**0.056**	**-2.609**	**-0.366**
landform_dist20 : early SPEI	-0.866	0.783	0.269	-1.993	0.262
landform_dist30 : early SPEI	-0.513	0.783	0.513	-1.640	0.615
landform_sink1 : early SPEI	**-2.470**	**0.779**	**0.002**	**-3.592**	**-1.348**
landform_sink2 : early SPEI	**-2.553**	**0.797**	**0.001**	**-3.700**	**-1.406**
landform_sink3 : early SPEI	**-2.594**	**0.840**	**0.002**	**-3.803**	**-1.384**
landform_temp : early SPEI	**-2.675**	**0.797**	**0.001**	**-3.822**	**-1.527**
landform_seasonal : USCV	1.864	7.142	0.794	-8.420	12.148
landform_dist10 : USCV	4.314	6.211	0.487	-4.630	13.258
landform_dist20 : USCV	1.916	6.267	0.760	-7.109	10.941
landform_dist30 : USCV	3.921	6.267	0.532	-5.104	12.946
landform_sink1 : USCV	-4.035	6.173	0.513	-12.925	4.854
landform_sink2 : USCV	**-16.658**	**6.241**	**0.008**	**-25.645**	**-7.670**
landform_sink3 : USCV	**-17.883**	**6.757**	**0.008**	**-27.612**	**-8.153**
landform_temp : USCV	-1.192	6.416	0.853	-10.431	8.047

Table C.11. Coefficient estimates from the final reduced model for soybean yield from the all farmable land scenario. Intercept included landform_upland. Included are the coefficient estimates ($\hat{\beta}$), standard errors (SE), and lower (LCL) and upper (UCL) 85% confidence intervals. Bolded text rows indicate the 85% confidence limits did not include '0'.

Variable	$\hat{\beta}$	SE	p.value	LCL	UCL
(Intercept)	**28.885**	**5.284**	**0.000**	**21.269**	**36.502**
landform_seasonal	**-26.885**	**5.379**	**0.000**	**-34.630**	**-19.139**
landform_dist10	**-11.137**	**5.081**	**0.028**	**-18.454**	**-3.821**
landform_dist20	-5.008	5.134	0.329	-12.402	2.385
landform_dist30	-3.915	5.134	0.446	-11.309	3.478
landform_sink1	**-9.890**	**5.057**	**0.051**	**-17.173**	**-2.608**
landform_sink2	**-9.986**	**5.079**	**0.049**	**-17.300**	**-2.672**
landform_sink3	-4.411	5.164	0.393	-11.848	3.025
landform_temp	**-24.822**	**5.226**	**0.000**	**-32.348**	**-17.297**
early SPEI	**1.483**	**0.694**	**0.033**	**0.483**	**2.483**
winter SPEI	-0.105	0.596	0.860	-0.963	0.753
USCV	**12.907**	**7.701**	**0.094**	**1.807**	**24.007**
landform_seasonal : early SPEI	**-4.548**	**0.988**	**0.000**	**-5.970**	**-3.125**
landform_dist10 : early SPEI	**-3.546**	**0.962**	**0.000**	**-4.931**	**-2.162**
landform_dist20 : early SPEI	**-2.005**	**0.967**	**0.038**	**-3.397**	**-0.613**
landform_dist30 : early SPEI	-1.041	0.967	0.281	-2.433	0.351
landform_sink1 : early SPEI	**-4.908**	**0.962**	**0.000**	**-6.293**	**-3.523**
landform_sink2 : early SPEI	**-6.210**	**0.968**	**0.000**	**-7.604**	**-4.816**
landform_sink3 : early SPEI	**-5.239**	**0.995**	**0.000**	**-6.671**	**-3.807**
landform_temp : early SPEI	**-7.023**	**0.980**	**0.000**	**-8.434**	**-5.613**
landform_seasonal : winter SPEI	**-1.972**	**0.857**	**0.022**	**-3.206**	**-0.737**
landform_dist10 : winter SPEI	**-1.621**	**0.830**	**0.051**	**-2.816**	**-0.426**
landform_dist20 : winter SPEI	**-1.244**	**0.832**	**0.135**	**-2.442**	**-0.045**
landform_dist30 : winter SPEI	-0.917	0.832	0.271	-2.115	0.281
landform_sink1 : winter SPEI	**-2.473**	**0.831**	**0.003**	**-3.669**	**-1.277**
landform_sink2 : winter SPEI	**-4.773**	**0.838**	**0.000**	**-5.980**	**-3.567**
landform_sink3 : winter SPEI	**-4.835**	**0.865**	**0.000**	**-6.081**	**-3.589**
landform_temp : winter SPEI	**-3.204**	**0.846**	**0.000**	**-4.422**	**-1.986**
landform_seasonal : USCV	10.253	7.940	0.197	-1.180	21.686
landform_dist10 : USCV	5.270	7.473	0.481	-5.491	16.031
landform_dist20 : USCV	1.265	7.540	0.867	-9.592	12.123
landform_dist30 : USCV	2.589	7.540	0.731	-8.268	13.446
landform_sink1 : USCV	2.077	7.445	0.780	-8.644	12.798
landform_sink2 : USCV	-3.542	7.482	0.636	-14.316	7.233
landform_sink3 : USCV	**-18.212**	**7.641**	**0.017**	**-29.215**	**-7.209**
landform_temp : USCV	**18.935**	**7.702**	**0.014**	**7.844**	**30.026**

APPENDIX D. QUESTIONNAIRE

Farming Low or Wet Spots within Crop Fields

Dear Participant:

My name is Dustin Toy. I am a graduate student in the Natural Resources Management Department at North Dakota State University (NDSU). We are trying to examine a few aspects related to farming wet spots/sloughs/wetlands within agriculture fields that are not currently enrolled in a conservation program. We use "low spots" as a term for low-lying or wet areas in a crop field that, on an average year, may be wet one or multiple times during the cropping year and usually dry in the fall. During wet years, these types of wet spots have ponded water and may develop cattails, rushes, or reeds after multiple years. When extended dry periods occur, landowners/operators are usually able to burn, disk, mow, rip, or a combination of those techniques to prepare that area for planting and harvesting of crops. We would appreciate your input on the following questions regarding the low spots described above that occur on your land.

Because you are a farmer in eastern North Dakota, you are invited to participate in this research project. You will be one of approximately 30 or more people being interviewed for this study.

You may find it interesting and thought provoking to participate in the interview. If, however, you feel uncomfortable in any way during the interview session, you have the right to decline to answer any question(s), or to end the interview.

There are 28 questions and should only take about 15 minutes to complete. Your participation in this questionnaire is completely voluntary. There are no penalties for not participating or ending your participation at any time. No personal identifying information of yours will be linked to this research.

If you have any questions about the study, please contact me (701-368-1870, dustin.toy@ndsu.edu), or contact my advisor (Edward "Shawn" DeKeyser, 701-231-8180, edward.dekeyser@ndsu.edu).

You have rights as a research participant. If you have questions about your rights or complaints about this research, you may talk to the researcher or contact the NDSU Human Research Protection Program at 701.231.8995, toll-free at 1-855-800-6717, by email at ndsu.irb@ndsu.edu, or by mail at: NDSU HRPP Office, NDSU Dept. 4000, P.O. Box 6050, Fargo, ND 58108-6050.

Thank you for your time and taking part in this research. If you wish to receive a copy of the results, please let me know after the interview.

1. What is your relationship to the farm? (indicate all that apply)
   __ Owner/Co-owner
   __ Decision maker
   __ Operator
   __ Renter
   __ other - _____________
2. How many total acres do you farm? ______
3. How many acres do you pay rent on for farming? ______
4. How many acres do you rent out to others for farming? _____
5. How would you describe the topography of the **majority** of your fields? (choose one)
   __ Flat
   __ Gently rolling
   __ Rolling
   __ Steep
   __ Other - ________
6. Approximately, how many acres of low spots do you actively **manage** (disk, burn, mow or spray) in preparation to try to plant a crop during a

Year	Acres
dry	
average	
wet	

7. Approximately, how many of acres of low spots do you **get seeded** with a crop during the following types of years?

Year	Acres
dry	
average	
wet	

8. What factors affect your decision to attempt to farm a low spot in your ag field? (Rank your top 3 and check any others that you consider)
   __ ability to get equipment in wet/low spot
   __ how frequent the wet/low spot has been wet in the past
   __ benefits of leaving them for wildlife
   __ remove vegetation to keep wildlife out of the area
   __ reduce insect habitat
   __ keep wet/low spots qualified for prevent plant insurance
   __ amount of time to prepare the area
   __ size or the wet/low spot
   __ farming history (yield or lack of yield) of the wet/low spot
   __ "other"_______________________________

9. Assuming a low spot has already been prepared (disked, burned, ripped) for planting, how often do you **seed or plant** these low spots?
   a. _______year(s) out of 10 years

10. Assuming a low spot has already been prepared (disked, burned, ripped) for planting, how often do you **harvest** a crop from these low spots?
   a. _______year(s) out of 10 years
11. Do you use precision agriculture technology/equipment (check all that apply)?
   __Yield monitor
   __variable rate seeding
   __variable rate spraying
   __prescription maps

12. What is your approximate average yield per acre across your farming operation? (leave blank if you do not plant that crop and add other crops if you plant them)

Crop	bushels/acre
Corn	
Soybeans	
Wheat	
Sunflowers	

13. When harvesting a crop in a low spot, how does the **yield typically compare** to the yield of an equally sized area of the surrounding field?

a lot higher	higher	about the same	lower	a lot lower

14. How much does it **cost to prepare** a low spot for planting compared to an equally sized area in the surrounding field?

a lot higher	higher	about the same	lower	a lot lower

15. Would you attempt to farm a 2-acre low spot if you **lost money** on that area over the indicated time period? You broke-even on the remaining years of the indicated time period.

3 of last 10 years	yes	no
5 of last 10 years	yes	no
7 of last 10 years	yes	no

16. Would you attempt to farm a 2-acre low spot if you **broke-even** financially on that area over the indicated time period? You lost money on the remaining years of the indicated time period.

3 of last 10 years	yes	no
5 of last 10 years	yes	no
7 of last 10 years	yes	no

17. Would you attempt to farm a 5-acre low spot if you **lost money** on that area over the indicated time period? You broke-even on the remaining years of the indicated time period.

3 of last 10 years	yes	no
5 of last 10 years	yes	no
7 of last 10 years	yes	no

18. Would you attempt to farm a 5-acre low spot if you **broke-even** financially on that area over the indicated time period? You lost money on the remaining years of the indicated time period.

3 of last 10 years	yes	no
5 of last 10 years	yes	no
7 of last 10 years	yes	no

19. Would you attempt to farm a 20-acre low spot if you **lost money** on that area over the indicated time period? You broke-even on the remaining years of the indicated time period.

3 of last 10 years	yes	no
5 of last 10 years	yes	no
7 of last 10 years	yes	no

20. Would you attempt to farm a 20-acre low spot if you **broke-even** financially on that area over the indicated time period? You lost money on the remaining years of the indicated time period.

3 of last 10 years	yes	no
5 of last 10 years	yes	no
7 of last 10 years	yes	no

21. Have you ever enrolled in a conservation program? If yes, check all that apply

__ I have never enrolled in a conservation program.
__Wetland Reserve Program (WRP)
__Conservation Reserve Program (CRP)
__Conservation Reserve Enhancement Program (CREP)
__Conservation Stewardship Program (CSP)
__Wildlife Habitat Incentive Program (WHIP)
__Agriculture Water Enhancement Program (AWEP)
__Environmental Quality Incentives Program (EQIP)
__Water Bank Program (WBP)
__Other (please list) - ___________________________

22. What is your age? ____
23. Are you currently married? ____
24. How many children do you have? ____
25. What percentage of your household income comes from farming? _____%
26. How many **people** does the farm currently employ? ____
27. How many **family members** does the farm currently employ? _____
28. What is the highest education level you have achieved?
a. GED b. High School c. College/Technical School d. Graduate School
29. Comments

____
____
____
____
____
____
____

APPENDIX E. CHAPTER 5 SUPPLEMENTAL MATERIALS

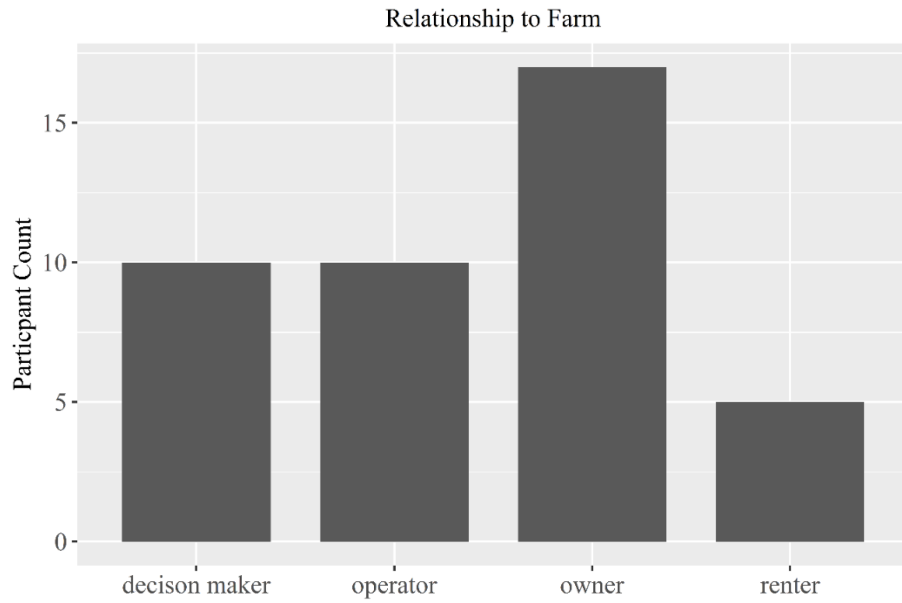

Figure E.1. Count of respondents on what they consider their relationship is to their farm.

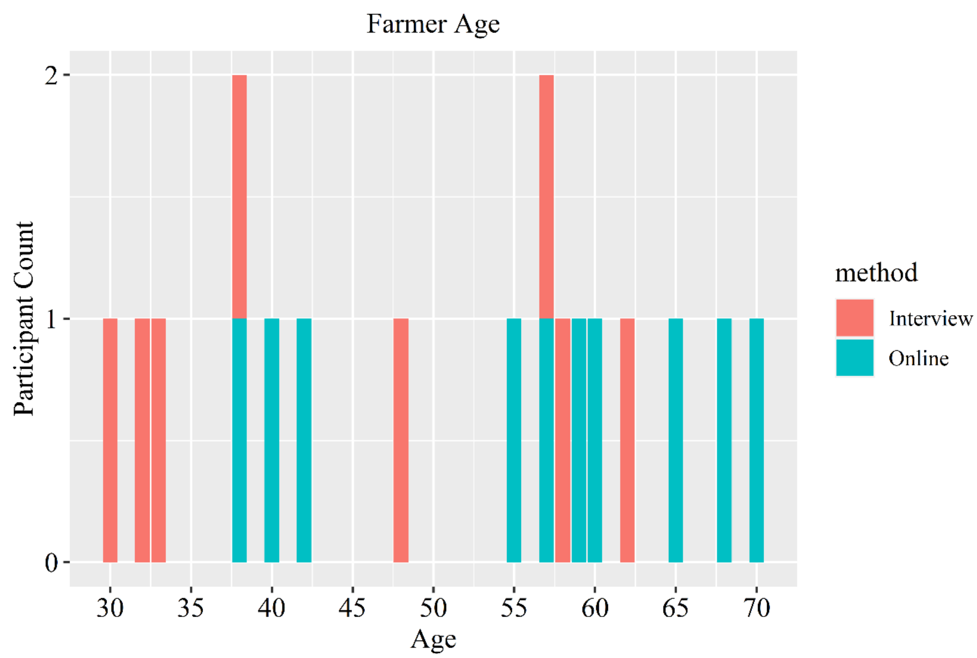

Figure E.2. Count of respondents for each age between 30–70 years. Colors indicate survey method.

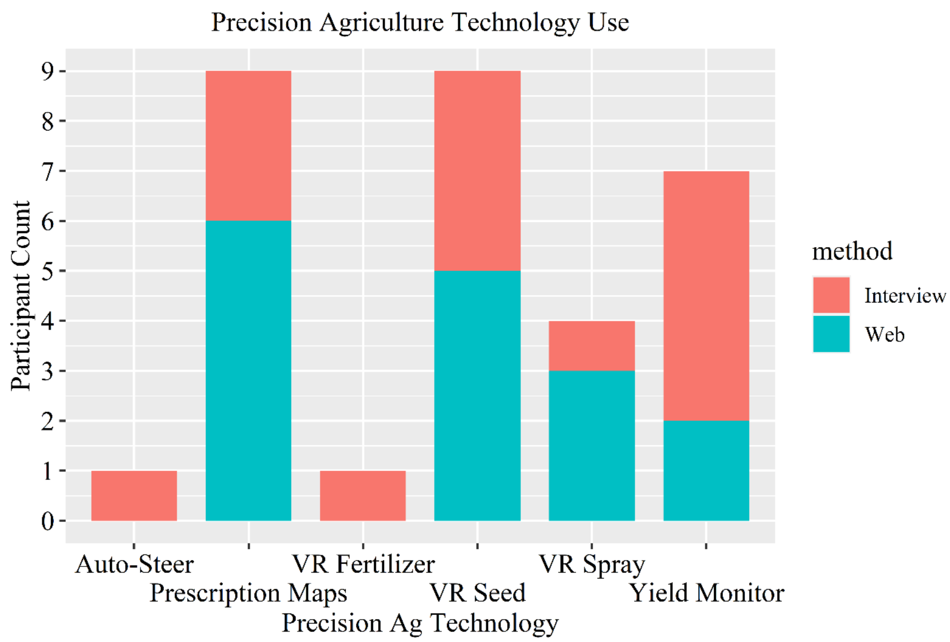

Figure E.3. Count of respondents who use precision agriculture technologies. These technologies are intended to enhance farming efficiency and track sub-field level inputs and yield. Variable rated = VR. Colors indicate survey method.

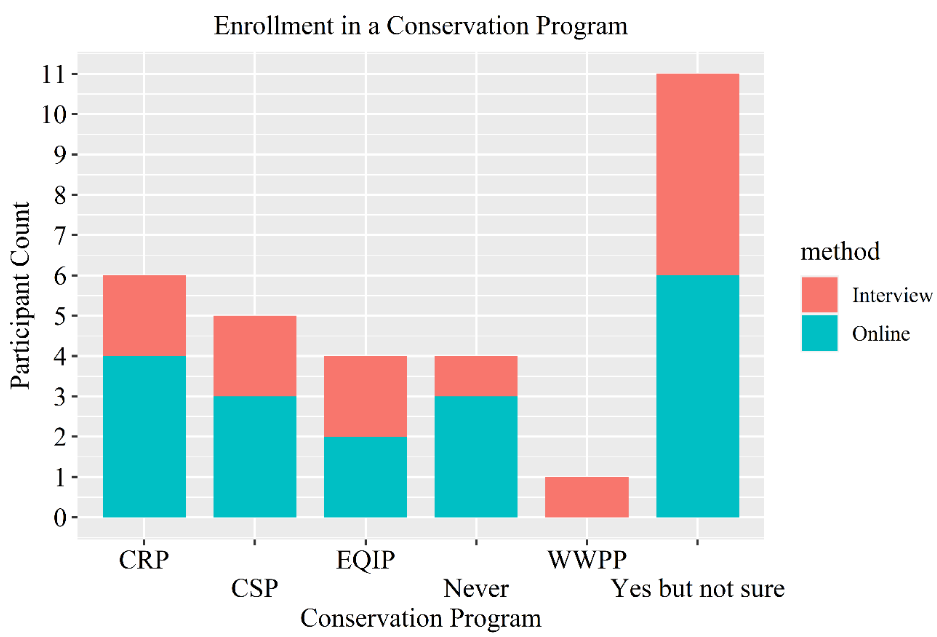

Figure E.4. Count of respondents that have enrolled in the following conservation programs: Conservation Reserve Program (CRP), Conservation Stewardship Program (CSP), Environmental Quality Incentives Program (EQIP), 'Never' enrolled in a program before, Working Wetlands Pilot Project (WWPP), and 'Yes but not sure' which program. Colors indicate survey method.

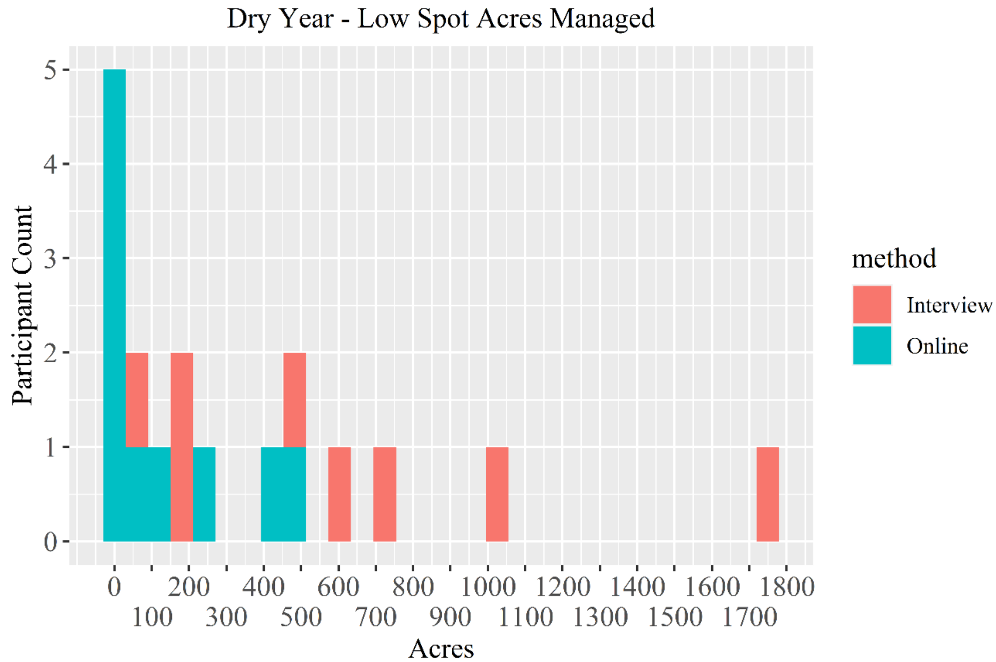

Figure E.5. Count of respondents regarding the number of acres of low spots they reported to actively manage (i.e., burned, disked, mowed, sprayed) in preparation to plant a crop during a dry year. Colors indicate survey method.

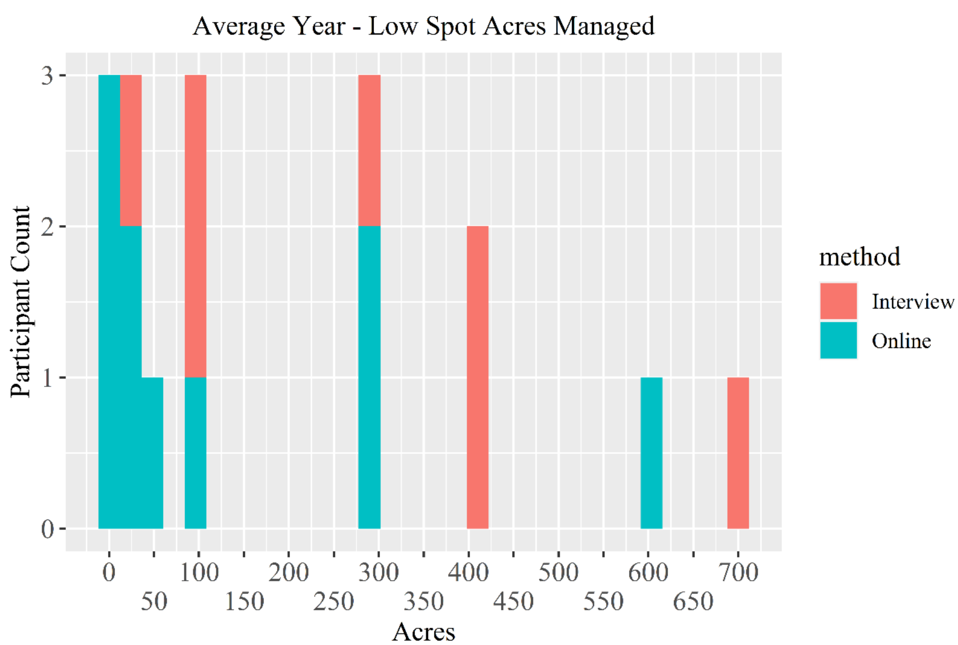

Figure E.6. Count of respondents regarding the number of acres of low spots they reported to actively manage (i.e., burned, disked, mowed, sprayed) in preparation to plant a crop during an average year. Colors indicate survey method.

Figure E.7. Count of respondents regarding the number of acres of low spots they reported to actively manage (i.e., burned, disked, mowed, sprayed) in preparation to plant a crop during a wet year. Colors indicate survey method.

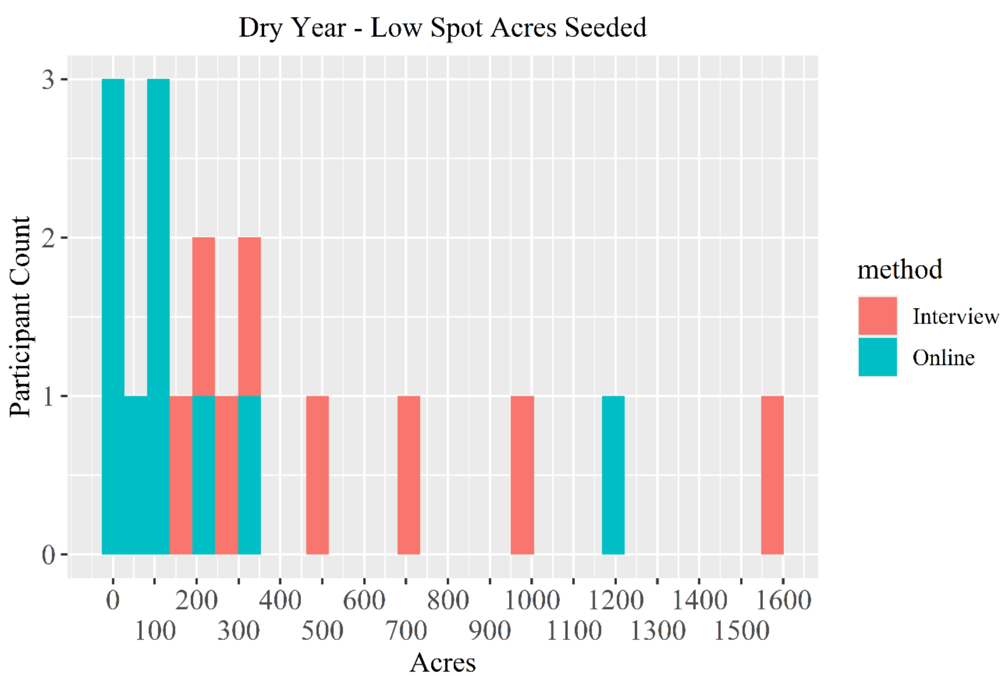

Figure E.8. Count of respondents regarding the number of acres of low spots they reported to get planted/seeded during a dry year. Colors indicate survey method.

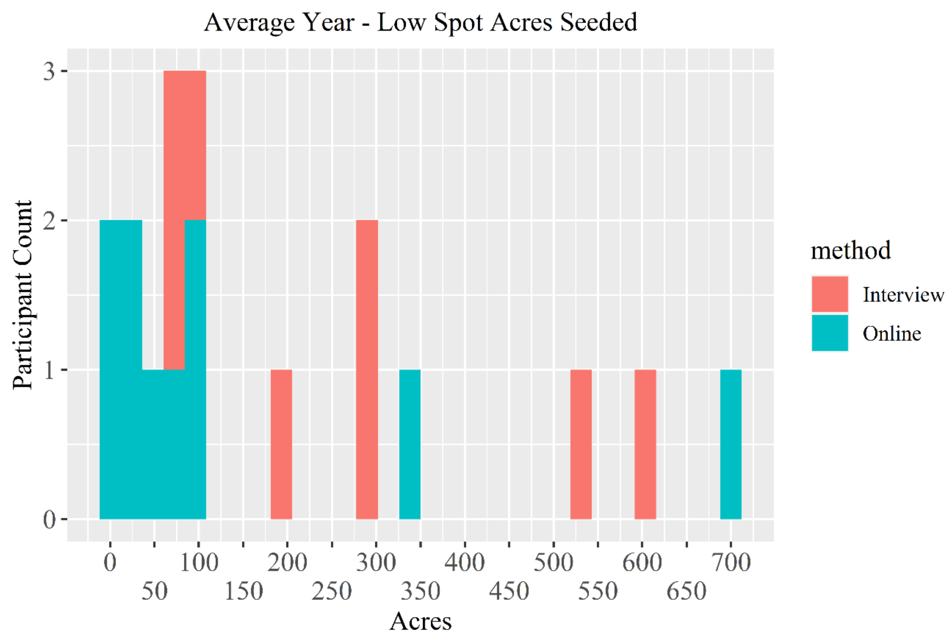

Figure E.9. Count of respondents regarding the number of acres of low spots they reported to get planted/seeded during an average year. Colors indicate survey method.

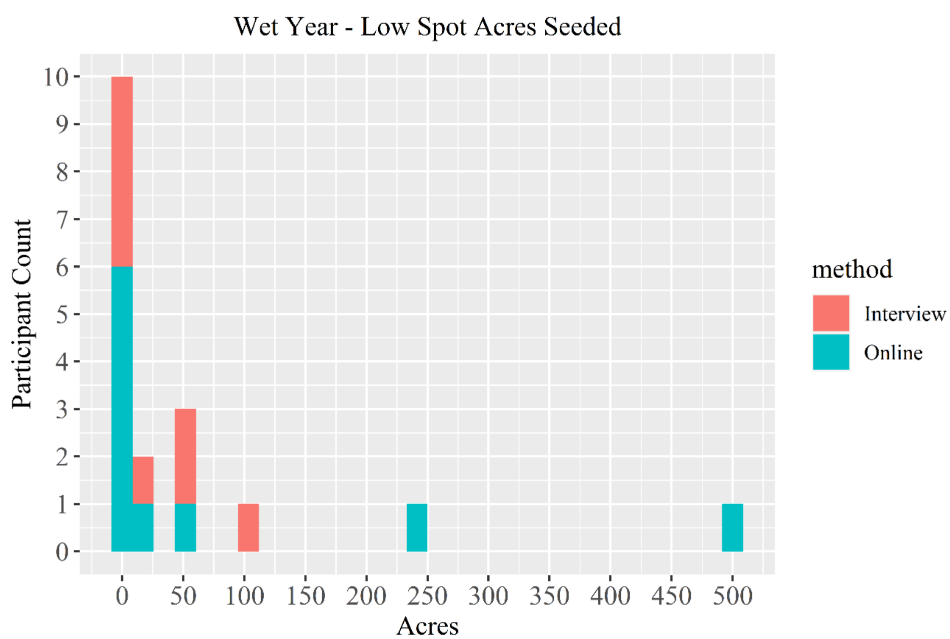

Figure E.10. Count of respondents regarding the number of acres of low spots they reported to get planted/seeded during a wet year. Colors indicate survey method.

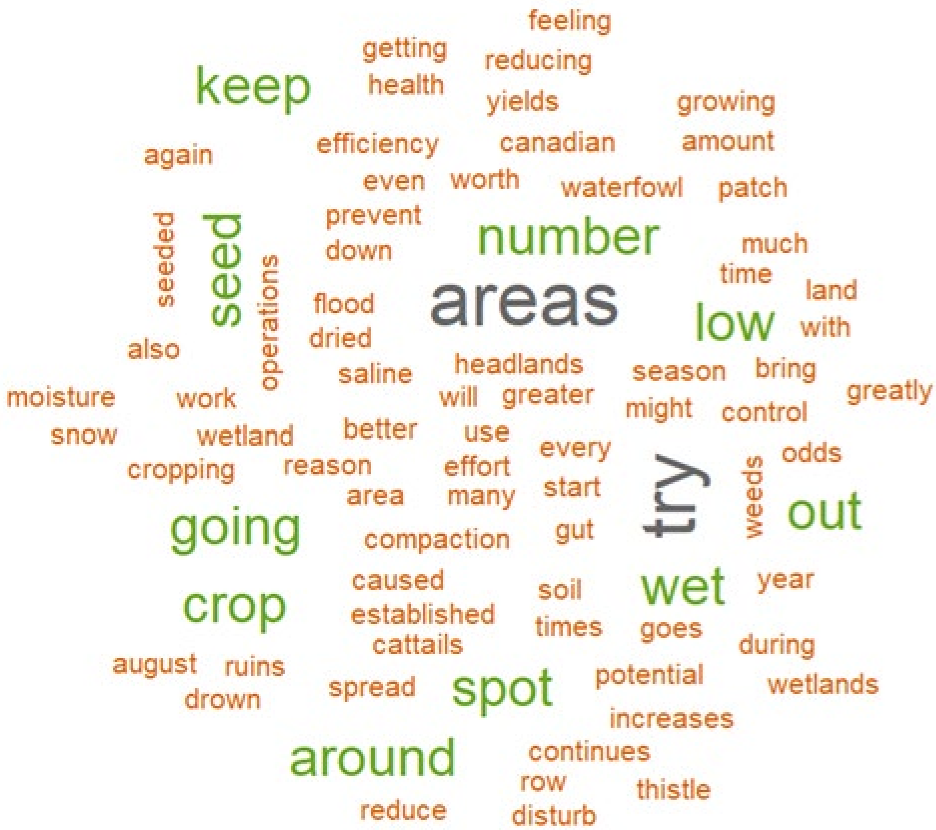

Figure E.11. Word cloud made from comments in the “other” category for the question about which factors influence farmers’ decisions whether to attempt to farm a low spot. Each word’s frequency of use in the comment section of this question was used to depict its color and its size. The minimum frequency used was one. Words that are black appeared more frequently than the other colors of words in this comment section. The larger words, such as “area” and “try”, were mentioned the most frequent in the comments.

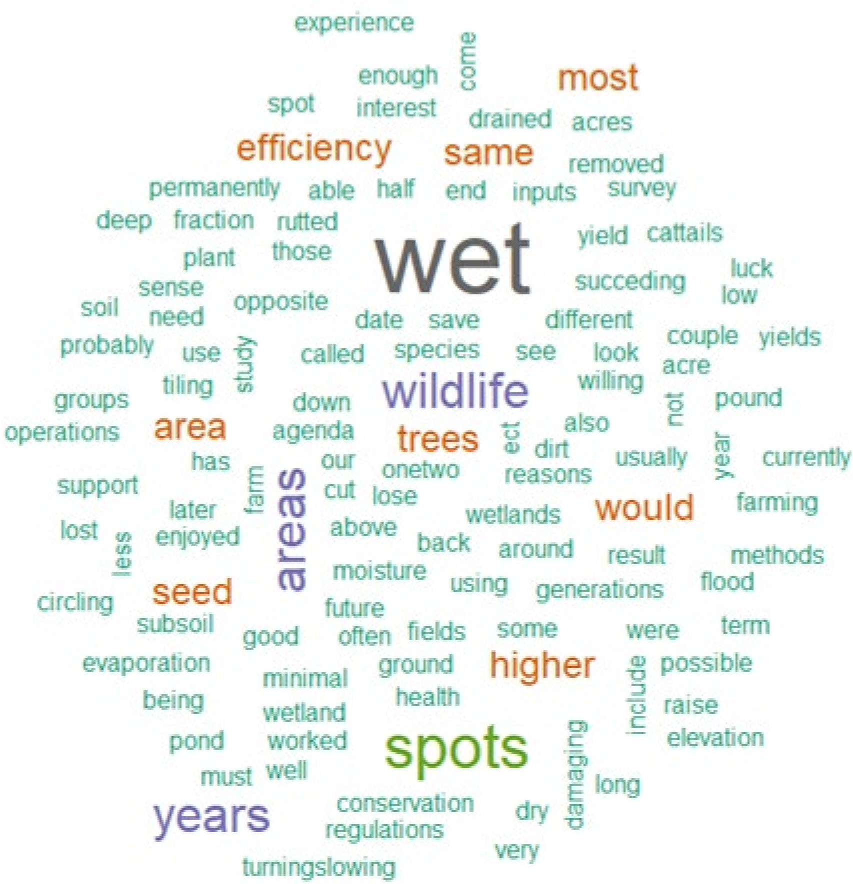

Figure E.12. Word cloud made from respondent-entered comments in the overall “comments” category from the online electronic form. Each word’s frequency of use in the comment section of this question was used to depict its color and its size. The minimum frequency used was one. Words that are black appeared more frequently than the other colors of words in this comment section. The larger words, such as “wet” and “spots”, were mentioned the most frequent in the comments.

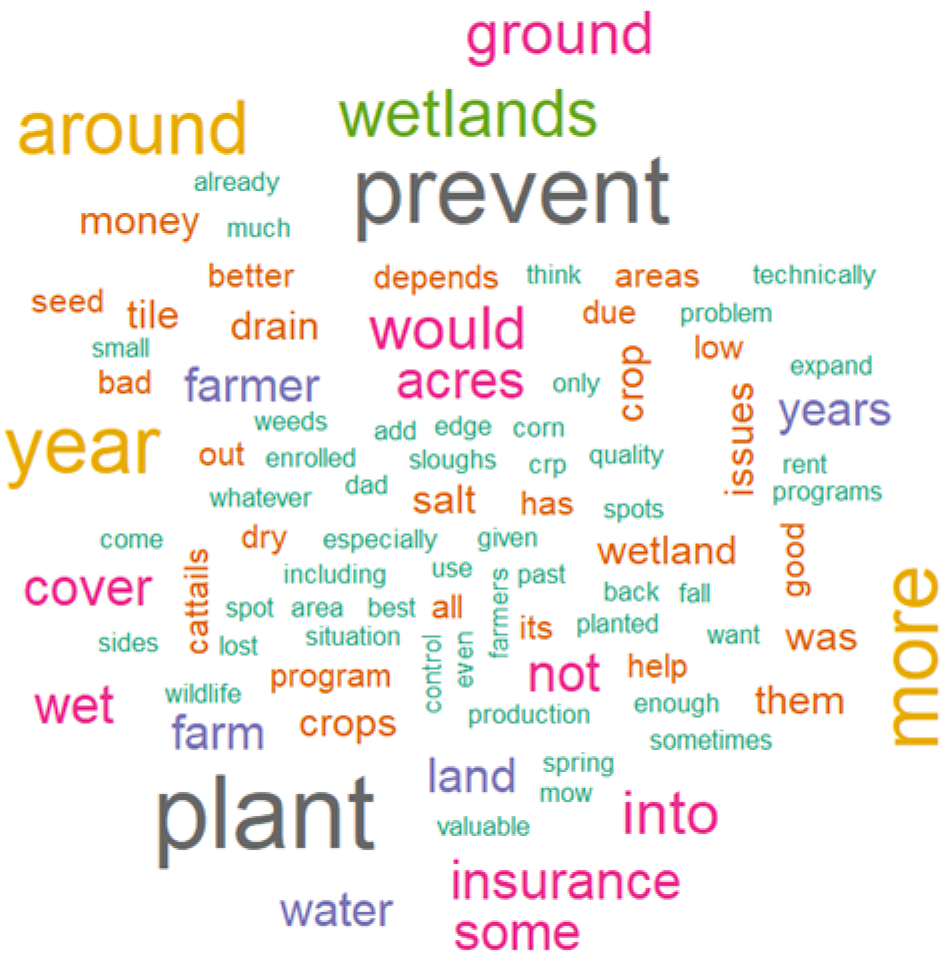

Figure E.13. Word cloud made from comments in the “other” category for the question about which factors influence farmers’ decisions whether to attempt to farm a low spot. Each word’s frequency of use in the comment section of this question was used to depict its color and its size. The minimum frequency used was two. Words that are black appeared more frequently than the other colors of words in this comment section. The larger words, such as “prevent” and “plant”, were mentioned the most frequent in the comments.

Table E.1. Table of self-entered comments from online respondents. Comments are listed as entered. Each row represented an individual respondent's comment.

Comments from Online Opt-in Questionnaire
NO
I WOULD LIKE TO SEE A STUDY USING A COUPLE DIFFERENT METHODS ON THESE LOW WET SPOTS, MAKE A POUND AND THE DIRT REMOVED RAISE AN AREA ONE-TWO ACRES ABOVE FLOOD ELEVATION AND PLANT TO DEEP RUTTED TREES. POND FOR EVAPORATION AND WILDLIFE AND SAME WITH THE TREES USE SUBSOIL MOISTURE AND WILDLIFE. WE NEED TO LOOK AT THESE SPOTS WITH A LONG TERM AGENDA TO SAVE THIS GROUND FOR FUTURE GENERATIONS.
THE WET AREAS MUST BE WORKED AS OFTEN AS POSSIBLE OR THEY ARE PERMANENTLY LOST TO THE WILDLIFE GROUPS THAT HAVE NO INTEREST IN FARM SUCCEDING.
SOME OF THE REASONS WE'RE WILLING TO LOSE ON THOSE SPOTS ALSO HAS TO DO WITH EFFICIENCY (TURNING,SLOWING DOWN ECT..)
OUR FIELDS ARE WELL DRAINED SO WE PROBABLY DO NOT MAKE SENSE TO INCLUDE IN THIS SURVEY. ON A WET YEAR WE MAY HAVE TO SEED AROUND A WET SPOT BUT ARE USUALLY ABLE TO COME BACK AND SEED IT AT A LATER DATE. CURRENTLY THERE ARE NO AREAS THAT ARE WE ENOUGH TO SUPPORT CATTAILS OR SUCH SPECIES. DRY YEARS WET AREAS = HIGHER YIELD OPPOSITE ON WET YEARS.
WETLAND CONSERVATION REGULATIONS ARE VERY DAMAGING TO SOIL HEALTH IN MY AREA OF ND. MOST OF THE SO CALLED WETLANDS ARE A FRACTION OF AN ACRE. IN WET YEARS, FARMING EFFICIENCY IS CUT IN HALF BY BEING BECAUSE MOST OF THE OPERATIONS END UP CIRCLING THESE SPOTS. MINIMAL TILING WOULD RESULT IN YIELDS THAT ARE 30 TO 40% HIGHER WITH THE SAME OR LESS INPUTS.
ENJOYED THIS EXPERIENCE! GOOD LUCK

Table E.2. Table of my paraphrased comments from the interviews conducted in-person. Comments are listed as they were recorded. Each row represented an individual respondent's comment.

My Paraphrased Comments from Interview
NEEDED TO CLARIFY Q#6. OWNER DOESN'T CARE ABOUT THE MONEY. IF WETLANDS ARE DRY THEN THEY WILL WORK THEM.
MORE THAN 1/3 OF OWNED ACRES WILL BE UNDER WATER NEXT YEAR. DAD HAD 320 ACRES IN AN AREA BUT CAN NOW ONLY FARM 150 DUE TO HIGH WATER. Q#7 WET YEARS CHANGE SO SURVEY ANSWERS ARE INFLUENCED BY YEARS THAT THEY FARMED. Q#8 FARMERS SAID THAT THEY MAY STILL TECHNICALLY FARM IT BUT PUT A COVERCROP THAT MAY HELP WITH WATER AND SALT ISSUES. Q#11 THIS FARMER MANUALLY ADJUST SPRAY BUT NOT TECHNICALLY DOING VARIABLE RATE. MORE LIKELY TO FARM A SMALL WET SPOT RATHER THAN DRIVING AROUND IT. Q#15 ON A 20 ACRE WETLAND THEY MAY FARM AS MUCH OF THE EDGE AS POSSIBLE - IF LOST MONEY 10/10 YEARS THEN THE GROUND IS JUST BAD. - 20 ACRES SPOT MORE TO DO WITH KEEPING UP PREVENT PLANT ACRES AND BAD GROUND LIKELY DUE TO SALT ISSUES. PREVENT PLANT GIVES FALSE HOPE AND IS INCENTIVISING FARMING POOR GROUND.
#15-20 ASKED IF THIS WAS PRODUCTION ACRES VS INCLUDING CROP INSURANCE. TOLD THEM, WHATEVER YOU WOULD DO NORMALLY. HOW YOU WOUL DO IT GIVEN CURRENT SITUATION AND HOWEVER YOU THINK ABOUT IT. - #6&7 WATER LEVELS SHIFT PERCEPTION OF WHAT A WET YEAR IS. - PREVENT PLANT IS A VICIOUS CYCLE. USED MORE FOR PURELY MONEY MAKING. PP FACTORS INTO RENTING ESPECIALLY. PP WOULD BE BETTER IF IT WAS MORE LIMITED. MAYBE AN OPTION COULD BE SOMETHING INCLUDING AN ALTERNATIVE SUCH AS DRAIN TILE. BETTER TO ADDRESS THE SITUATION DIRECTLY WITH DRAIN TILE THAN TO USE A BAND-AIDE LIKE PP INSURANCE. THE WET GROUND GETS SALTY AND THEN NOT WORTH FERTILIZING. PEOPLE WILL DO WHATEVER TO RESET PP INSURANCE SUCH AS DROP SEED COUNT REALLY FAR DOWN. PP CHECK THIS PAST YEAR WAS ENOUGH TO COVER ALL PREMIUMS OF THEIR INSURANCE PLUS SOME. FARMERS USE WHATS AVAILABLE EVEN PP. WOULD BE INTERESTED IN A DIFFERENCT PROGRAM. COVER CROPS COULD HELP WITH WATER ISSUES.
AS NEARING RETIREMENT, THEY WOULD LIKE TO ENROLL SOME OF THE BIG LOW SPOTS INTO CRP OR CONSERVATION PROGRAM.
Q#2-4 ADD CROPLAND, DON'T INCLUDE PASTURE. CONSIDER REPHRASING; DOES HAVE SOME TILE DRAIN THAT GOES AROUND WETLANDS.; FARMER DESPISES CATTAILS AS A FARMER. HAVE A LOT OF CATTAILS. ONCE CATTAILS GET A HOLD, ITS HARD TO GET RID OF THEM. THEN THE WETLANDS DON'T DRY AS QUICKLY. THEN EXPAND OUT. TAKES YEARS TO GET THAT FARMLAND BACK.; WILDLIFE ADAPT TO WHAT HABITAT/COVER THERE IS.; Q9&10 ADD ASSUMING ALREADY PLANTED.; LOOK UP PAUL GALPERN - U OF CALGARY; Q#15-20 SOME AREAS THEY DON'T TRY AROUND WETLANDS DUE TO ALKALINITY. WANT MORE QUALITY GROUND. THEY PLANT COVER CROPS IN ALKALI AREAS & LOW PRODUCING AND THEN GRAZE CATTLE IN FALL AND SPRING. COVER CROPS ARE THE LATEST CRAZE. TOUGH TO GET COVER CROP ESTABLISHED AFTER SOYBEANS. THEY DO SEED RYE AFTER CORN. ORGANIC MATTER THEY'VE FOUND HAS THE HIGHEST CORRELATION TO INCREASED YIELDS.; LOOKING INTO CSP PROGRAM; DRAIN TILE AROUND A COUPLE WETLANDS; CONSIDERS HIMSELF A STEWARD OF THE LAND; LIKES WILDLIFE AND WETLANDS; IT WOULD BE GOOD IF MORE PROGRAMS PUSHED COOPERATIVE PROGRAMS WITH LANDOWNERS

Table E.2. Table of my paraphrased comments from the interviews conducted in-person (continued). Comments are listed as they were recorded. Each row represented an individual respondent's comment.

My Paraphrased Comments from Interview
ONLY DISKED UP WHEAT STUBBLE THIS PAST YEAR. HAD 800 ACRES OF PREVENT PLANT, WHICH WAS MORE THAN EVER.;Q#9 SOMETIMES GROUND IS PREPARED IN THE SPRING OR FALL. INSURANCE DATES COME INTO PLAY. NOT A VALUABLE NUMBER GIVEN SINCE IT DEPENDS SO MUCH ON THE YEAR.; Q#10 NOT A VALUABLE ANSWER EITHER. FARMER CAN UNDERSTAND WHY I THINK THIS WOULD BE EASY TO COME UP WITH AND USEFUL.; Q#12 LAST YEAR WASN'T A GOOD YEAR FOR CROP PRODUCTION. DIDN'T GET ENOUGH HEAT UNITS.; Q#13 VARIES BY YEAR. DRY YEAR WILL OUTPERFORM THE REST OF THE GROUND. AVERAGE OR WET YEAR WILL BE SAM OR A LITTLE LESS. MIGHT HAVE SOME QUALITY ISSUES.; Q#14 WEEDS PLUG DIGGER SO MAY HAVE TO MOW FIRST.; Q#16 ONE REASON IS BECAUSE FARMER HAS TO MAKE A GOOD FAITH ATTEMPT TO FARM. LEAVING WETLANDS LENDS TO MORE WEEDS AND THEN THEY EXPAND. ATTEMPTING TO CONTROL THEM KEEPS THEM SMALL.; Q#17 REQUIRED BECAUSE OF INSURANCE AND ECONOMICS. PAYING RENT ON LAND AND IF NOTHING IS DONE WITH THOSE THEN YOU HAVE ALREADY LOST MONEY. THERE ARE 2 SIDES TO IT THOUGH, I.E., TO WHAT EXTENT DO YOU WANT TO IMPROVE LAND THAT YOU RENT?. MAY END UP TALKING TO THE RENTER AND ASKING IF THEY WOULD TAKE THE UNPRODUCTIVE LAND OUT OF THE AGREEMENT. THEY MAY OR MAY NOT.; IT'S IN OWN BEST INTEREST TO GET INTO ALL RENTED LAND. MAY HAVE TO DO MORE SUCH AS WEED CONTROL EVEN IF YOU GET THE WETLAND SEEDED.
Q#6&7 - MAYBE REPHRASE TO "WET IS GENERALLY FEWER OR LOWER"; Q#13 - BEST DIRT IS IN THE BOTTOM OF SLOUGH IF YOU CAN GET TO IT. SALT AROUND THE EDGES OF SLOUGHS IS A PROBLEM. PART OF THE PLANTED AREA USUALLY DROWNS OUT.; Q#14 - EXPENSIVE TO GET INTO WETLANDS WHEN YOU MOW DISK AND BURN. Q#18 - DEPENDS ON PREVENT PLANT LAWS. PREVENT PLANT IS THE DIFFERENCE IN THESE LOW SPOTS. ALSO DEPENDS ON THE POSITION OF THE WETLAND WITHIN THE FIELD, I.E., WHETHER ITS ON THE EDGE AND EASIER TO GO AROUND OR IN THE MIDDLE WHEN YOU HAVE TO GO AROUND ALL SIDES. SOMETIMES BETTER TO JUST GO THROUGH THE WETLAND THAN DRIVE AROUND, ESPECIALLY WITH A CORN CROP.; DAD HAS ENROLLED PREVIOUSLY IN EQIP & WBP.; SALT AROUND SLOUGHS IS A BAD PROBLEM SO THEY STARTED TO SEED SOME COVER CROPS IN THE ALKALINE AREAS TO HELP WITH THE SALTS.; BEEN TRYING TO GET INTO THE CRP FOR 3 YEARS, NOT SURE WHY THEY HAVEN'T GOTTEN ENROLLED. HASN'T HEARD BACK FROM THEM.

Table E.3. Table of the comments from the ‘other’ section for the question, “What factors affect your decision to attempt to farm a low spot in your ag field”? Comments are listed as they were entered by the respondents. Each row represented an individual respondent’s comment.

Decision Factors Comment Section
REDUCE THE NUMBER OF HEADLANDS FOR ROW CROP OPERATIONS
#1 REASON I TRY TO SEED THEM EVERY YEAR EVEN IF IS IN AUGUST, USE THE MOISTURE TO KEEP THE SPOT FROM GOING SALINE\n#2 CONTROL WEEDS, MANY TIMES THIS WILL BE THE START OF A CANADIAN THISTLE PATCH AS WATERFOWL BRING IN SEED
TO TRY TO KEEP DOWN THE AMOUNT OF SNOW IN LOW AREAS
RUINS LAND AROUND THE WETLAND AND CONTINUES TO SPREAD
NUMBER 1. CROPPING LOW AREAS GREATLY INCREASES EFFICIENCY AND YIELDS. ALSO, SOIL HEALTH IS MUCH BETTER BY REDUCING COMPACTION CAUSED BY GOING AROUND AREAS. \n
X - WHAT THE POTENTIAL IS FOR THE WET SPOT TO FLOOD OUT DURING GROWING SEASON.
2 - THE GUT FEELING OF WORTH THE TIME AND EFFORT TO DISTURB DRIED UP WET AREA, OR IS ODDS OF JUST DROWN OUT AGAIN GREATER.
X - I TRY TO WORK THE WETLANDS TO PREVENT CATTAILS FROM GETTING ESTABLISHED
X- GOES WITH #3-WHAT CROP IT MIGHT GET SEEDED WITH