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The Impact of Agriculture on Waterfowl Abundance: Evidence from Panel Data

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Abstract

Agricultural expansion and intensification in Canada's Prairie Pothole Region (PPR) have contributed to declining waterfowl populations since the 1970s. Although this region represents a mere 10% of North America's waterfowl breeding habitat, it produces over 50% of the continent's duck population and roughly 60% of Canada's agricultural output. Thus, intense competition exists between private economic interests and public benefits in the PPR. To better understand the conflict between agricultural and wildlife uses of land, panel methods are used to examine the spatiotemporal variation of waterfowl populations and agricultural land use intensity in the PPR from 1961-2006. For the main static model, we find that a one percent increase in cropland or pasture decreases duck density by 6%, while a similar increase in summerfallow area decreases duck density by 7%. Estimates based on a dynamic specification are more conservative. For the lagged dependent variable model, a 1% increase in cropland and pasture decreases duck density by 4.6%, while a decline of 4.7% is predicted for increases in summerfallow area. The spatial autoregressive model allows the derivation of measures for assessing direct and indirect impacts. The estimated direct impacts fall between those obtained from the standard and dynamic models, but, when spillover effects are included, the impacts exceed those predicted by the standard model. It would appear that conserving wetlands in one location has the added benefit of increasing productivity of wetlands at other locations.

Keywords: wetlands protection; spatial econometrics; GIS; land use conflict; migratory waterfowl

JEL Classification: Q57, C33, Q15, Q24

1. Introduction

Canada's Prairie Pothole Region (PPR) represents a mere 10% of North America's waterfowl breeding habitat (Figure 1), but the region produces over 50% of the continent's duck population (Baldassarre et al. 1994). Since the PPR also accounts for roughly 60% of Canada's agricultural output (Statistics Canada 2006), intense competition exists between private economic interests and public benefits in this region. Not surprisingly, wetlands and waterfowl numbers have been in decline, and lie below levels considered socially desirable. North American waterfowl populations have fallen by as much as 40% since populations began to be monitored in the early 1950s (US Fish and Wildlife Service 2010b).

Using a bioeconomic model of waterfowl management in which wetlands only benefitted duck hunters, Brown and Hammack (1973) found that both wetlands area and waterfowl populations should be increased over historic levels. Nearly 40 years later, the situation had not changed: van Kooten, Withey and Wong (2011) found wetlands and duck numbers were well below their socially desirable levels, and that climate change and efforts to mitigate it through biofuel policies only served to widen the 'externality gap' (Withey and van Kooten 2011). Yet, duck populations have continued to experience periods of sharp decline since the mid 1970s.

Drought and climate change have likely been influential factors in bring about declines in waterfowl numbers, but habitat displacement and degradation from increased agricultural activity have also been an important cause. Due to the ecological and economic benefits of preserving wetlands and waterfowl, an empirical examination of the effects of agricultural land use on waterfowl populations is worthwhile, not only for understanding the potential intensity and significance of these effects, but also for gaining insights for management plans that seek to forestall habitat loss and population declines.

Various wetland conservation activities have been undertaken by public and private agencies since the 1890s (Porter and van Kooten 1993), but the establishment of the North American Waterfowl Management Plan (NAWMP) in 1986 constituted the first continental effort to restore waterfowl populations – to levels seen in the mid 1970s (CWS 2004). Since its inception, over $1.5 billion has been used in conservation efforts across Canada with more than half of these funds directed to the prairies (NAWMP Committee 2009). In the PPR where the overlap between the best waterfowl habitat and the best agricultural lands can be as high as 91 percent (Bethke and Nudds 1995), it is not surprising that the primary conservation strategy is land securement: "The protection of wetland and/or upland habitat through land title transfer or binding long-term (minimum 10-year) conservation agreements with a landowner" (NAWMP Committee 2009). To date, over six million acres has been secured and an additional two million acres targeted over the next 10 years (NAWMP Committee 2009).

This study does not aim to judge the effectiveness or efficiency of NAWMP programs (see van Kooten and Schmitz 1992; Porter and van Kooten 1993), but recognizes that an important step in any such evaluation is to explore the causal relationship between agricultural land use and waterfowl populations. Using linear panel models, we examine whether there is empirical support for the hypothesis that agricultural intensification impacts waterfowl populations negatively, and, if so, the potential extent of this impact given that migratory waterfowl can choose to breed where wetlands are more plentiful if wetlands at one location are lost or reduced.

The cross-sectional units used in the analysis are the US Fish and Wildlife Service's strata 26-40 (Figure 1). The timeframe under consideration is 1961-2006, as these are the years when census data are available. The panel data models employed in the analysis can be classified as standard, dynamic and spatial. For the main standard model, we find that a one percentage point increase in cropped farmland decreases duck density by 6%, while respective declines are 7% and 6% for increases in summerfallow and pasture area. The estimates from dynamic specifications are more conservative; for the lagged dependent variable model, a one percentage point increase in cropland or pasture is predicted to decrease duck density by 4.6%, and by 4.7% for a proportionally equivalent increase in summerfallow area.

Given that migratory waterfowl are mobile across the landscape, the spatial autoregressive model is important because it allows the derivation of measures for assessing direct and indirect impacts. The estimated direct impacts for the most conservative set of estimates fall between those obtained from the standard and dynamic models. However, when spillover effects are also included, the impacts exceed those predicted by the standard model. This suggests that models that ignore spatial aspects underestimate effects , and conserving wetlands in one location has the added benefit of increasing productivity of wetlands in producing waterfowl at other locations.

We begin our study in the next section by reviewing literature most relevant to our analysis. This is followed by a description of the data and data sources, the models, and the results. We conclude with empirically derived estimates of the potential value of waterfowl (ducks in our analysis) and some observations concerning future research needs.

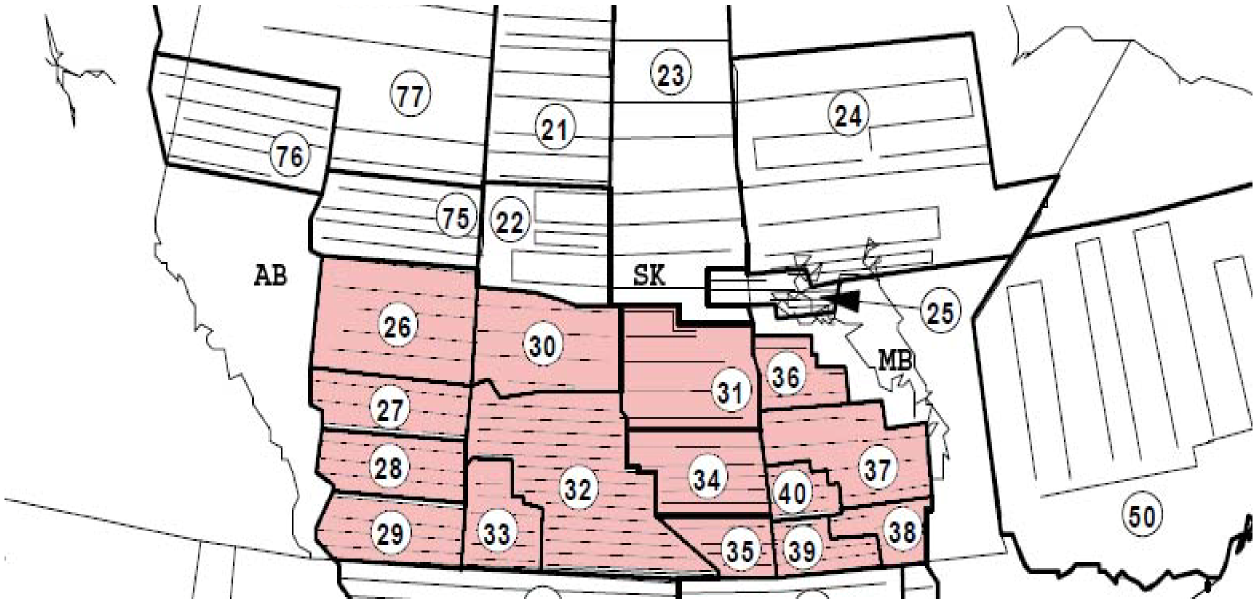

Figure 1: Transects and Strata of the Waterfowl Breeding Population and Habitat Survey (Source: Wilkins and Cooch 1999, p.38; US Fish and Wildlife Service 2010a, p.60)

2. Literature Review

This paper is loosely based on a study by Podruzny et al. (2002), who use random coefficient models, fixed effects models and various mixed specifications to examine the response of northern pintail ducks to changes in wetlands and agriculture in the PPR from 1961-1996. Their regression specifications model pintail density as a function of wetland density, climate variables (soil moisture and precipitation), and measures of agricultural land use intensity (percentages of improved farmland, pasture, cropland, etc.). Additionally, their analysis is conducted at various spatial scales (provincial-, stratum- and transect-levels) in order to obtain an understanding of possible multiscale effects.

We adopt a variation of Podruzny et al.'s (2002) general model and use many of the same covariates, but our analysis is much less ambitious as it examines effects at the stratum-level only. As discussed in more detail later, we are unable to justify the use of random effects and instead opt for fixed effects estimation. Although the title of Podruzny et al.'s (2002) paper suggests otherwise, they are not interested in determining the magnitude of the impact of agriculture and wetlands on pintail populations, perhaps because this species only accounts for ~5% of the total duck population in the PPR. Thus, they do not report any coefficient estimates, but focus on whether the covariates are statistically significant and the direction of the impact based on the signs of the slope estimates. They find that, in general, pintail density is positively related to pond density, precipitation and percent summerfallow, and negatively related to percent cropland and percent improved pasture. With the exception of pintails and a few other minor species, ducks rarely nest in crop or fallow land (Baldassarre et al. 1994); thus, although Podruzny et al. (2002) find a positive relationship between pintails and summerfallow, this result cannot be generalized and the relationship should be negative for waterfowl as a whole.

Bethke and Nudds (1995) also study the effects of climate and land use variables on duck populations. They examine ten species individually, but the model specifications are not reported in their paper. However, it is apparent that they examine climate and land use effects separately and run separate multivariate regressions for each species and stratum. As this approach does not take advantage of the information that can be gained from the panel structure of the data, it is inefficient (Wooldridge, 2002). In addition, their OLS estimators likely have considerable bias, because relevant regressors that are likely correlated with their predictor variables have been omitted from the models. Although we do not follow the unit-by-unit approach of Bethke and Nudds (1995), the variables used in their study are similar to those chosen by Podruzny et al. (2002) and for the current study, and are thus useful for comparing results. With regards to the effects of agricultural land use, Bethke and Nudds (1995) find that the resulting habitat loss accounted for 65% and

80% of the variation in mallard and northern pintail population deficits, respectively. (As noted, northern pintail are a minor species while mallards account for about one-quarter of all ducks.) No significant relationship was detected for the other species.

In an examination of mallards, Miller (2000) takes a slightly different approach by using a log transformed index of production (the ratio of immature to mature mallards) instead of population density or numbers as the dependent variable. The suite of potential predictor variables is similar to that chosen by Bethke and Nudds (1995) and Podruzny et al. (2002), and Miller (2000) expands his analysis to include regions in the United States. His approach is pooled OLS with models examined at two spatial scales: the stratum scale and the continental (Canada's PPR) scale. Similar to Bethke and Nudds (1995), Miller also finds a negative relationship between cropland and mallard production at the stratum level. However, at the continental level, the relationship is positive. He views this relationship as spurious, resulting from random error.

We also considered a pooled OLS regression model, but specification tests suggested that it was appropriate to allow for heterogeneity across units and time. Further discussion is provided in later sections.

3. Data

We used data compiled from surveys of wetland and waterfowl counts, drought indices derived from meteorological data, and agricultural censuses. This is discussed further below. Summary statistics appear in Table 1. For the static and dynamic models, data are first sorted by cross-section and then by time – 1961, 1966, etc. for stratum 26 followed by 1961, 1966, etc. for stratum 27, and so forth for each of strata 26-40 (Figure 1).

For the spatial models, data are first sorted by time and then by cross-section.

Waterfowl and Wetlands

Beginning in 1955, the US Fish and Wildlife Service (USFWS) and the Canadian Wildlife Service (CWS) have conducted annual ground and aerial surveys in May that provide counts of ponds and various waterfowl species. For the purposes of this survey, the PPR is divided into 15 strata, denoted as strata 26-40 in Figure 1. Figure 2 displays the time series for duck populations and pond counts for the entire PPR. These two series are highly correlated, and duck population movements appear to follow pond count movements. The close relationship between these two variables has been examined in depth in numerous studies; thus isolating the effect of wetland numbers on duck populations is not of particular interest here. Rather, we focus on whether wetland numbers moderate the effect of agricultural land use on duck populations.

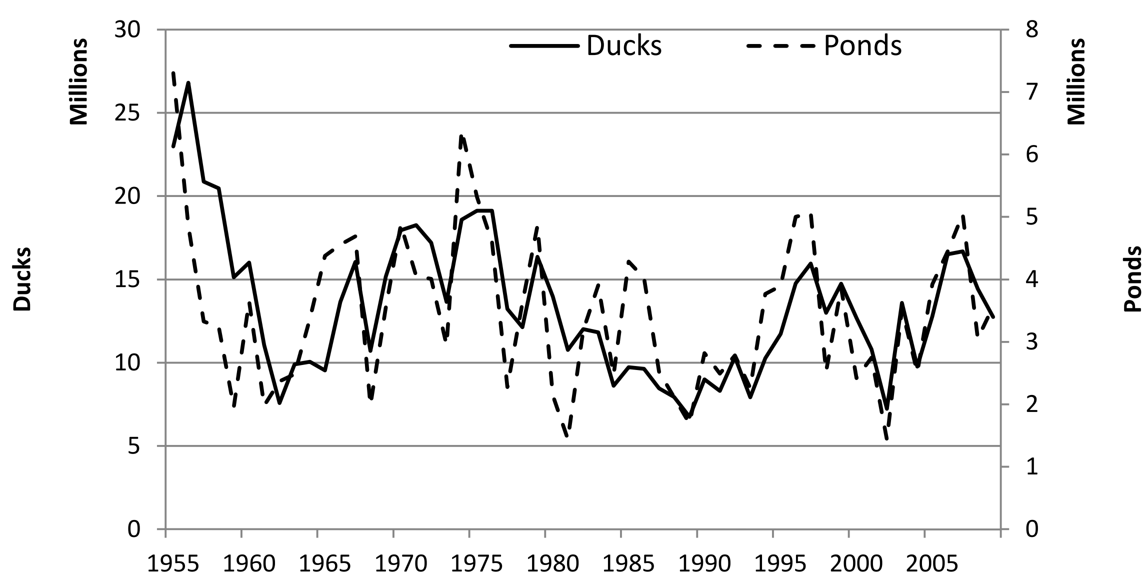

Figure 2: Duck Population and Pond Count Time Series, 1955-2009 (Source: USFWS 2010b)

Table 1: Panel Summary Statistics, 1961-2006

		Mean	Std. Dev.	Min	Max
Ducks	Overall	885,739.5	860,270.0	18,438.0	4,278,517.0
(number)	Between		768,571.9	69,543.8	2,562,622.0
	Within		430,164.8	-439,824.8	2,601,634.0
Ponds	Overall	235,632	193,852.4	23,103.0	1,041,420.0
(number)	Between		156,340.9	58,351.0	513,210.7
	Within		120,882.9	-153,958.5	763,841.3
% Cropland[a]	Overall	37.695	14.451	6.266	67.868
	Between		13.509	8.930	61.951
	Within		6.113	22.626	48.895
% Fallow[a]	Overall	11.861	7.568	0.312	28.947
	Between		6.203	1.736	23.696
	Within		4.596	-1.076	22.996
% Pasture[a]	Overall	3.475	2.211	0.275	12.509
	Between		1.451	0.965	7.329
	Within		1.707	-2.311	8.655
SPI-1 Month	Overall	-0.132	0.981	-3.720	1.910
	Between		0.197	-0.416	0.197
	Within		0.962	-3.458	1.828
SPI-12 Month	Overall	0.142	1.036	-3.720	2.430
	Between		0.260	-0.190	0.474
	Within		1.005	-3.425	2.515

Notes: Each variable has 150 total observations across 15 strata over 10 time periods.
[a] Percentage of total farm area.

Agricultural Data

Agricultural land use data were obtained from the Census of Agriculture, which is conducted by Statistics Canada every five years since 1961. The most recent census was in 2006 (Statistics Canada 2006). Data for individual Census Consolidated Subdivisions (CCS) were assigned to survey strata using the ArcGIS software package and aggregated to obtain three measures of agricultural land use intensity: proportions of farm area used as cropland, summerfallow and improved pasture (Table 1). Time series of cropland acreage and waterfowl numbers for the PPR appear in Figure 3. This figure illustrates a possible negative relationship, especially after the 1970s.

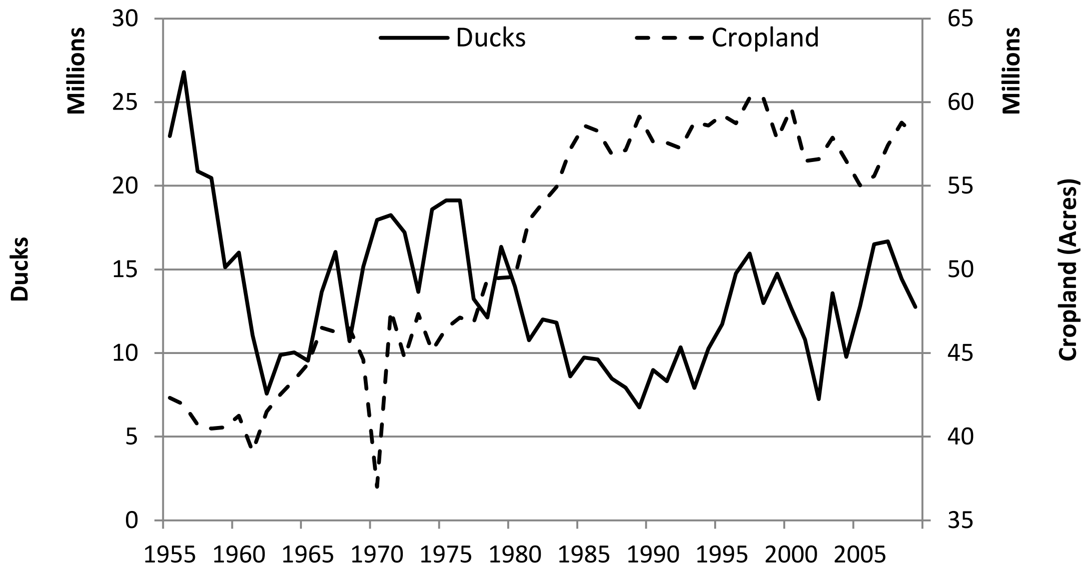

Figure 3: Cropland Acreage and Duck Count Time Series

The overlay of Statistics Canada's Census Consolidated Subdivisions and the USFWS's waterfowl strata boundaries dictate the assignment of CCS data to each stratum, as indicated in Figure 4. When a CCS overlies two or more strata, the acreage data were multiplied by the proportion of the CCS that falls within the stratum under consideration. To ensure consistency between years, we only consider CCS with observations in every census year, unless the missing observation was due to amalgamation for confidentiality reasons with a neighbouring CCS. To complicate this matter, the numeric identifiers for the CCS were changed by Statistics Canada in 1981; thus, we recoded the earlier years prior to performing ArgGIS database procedures.[1] This method revealed 446 CCSs that coincided with the PPR. Because Podruzny et al. (2002) indicated that 95% of the CCS boundaries

[1] The names of the CCS are also inconsistently formatted from year to year, so it could not be used as a key.

remain consistent over time, we simply assume that they do not change.

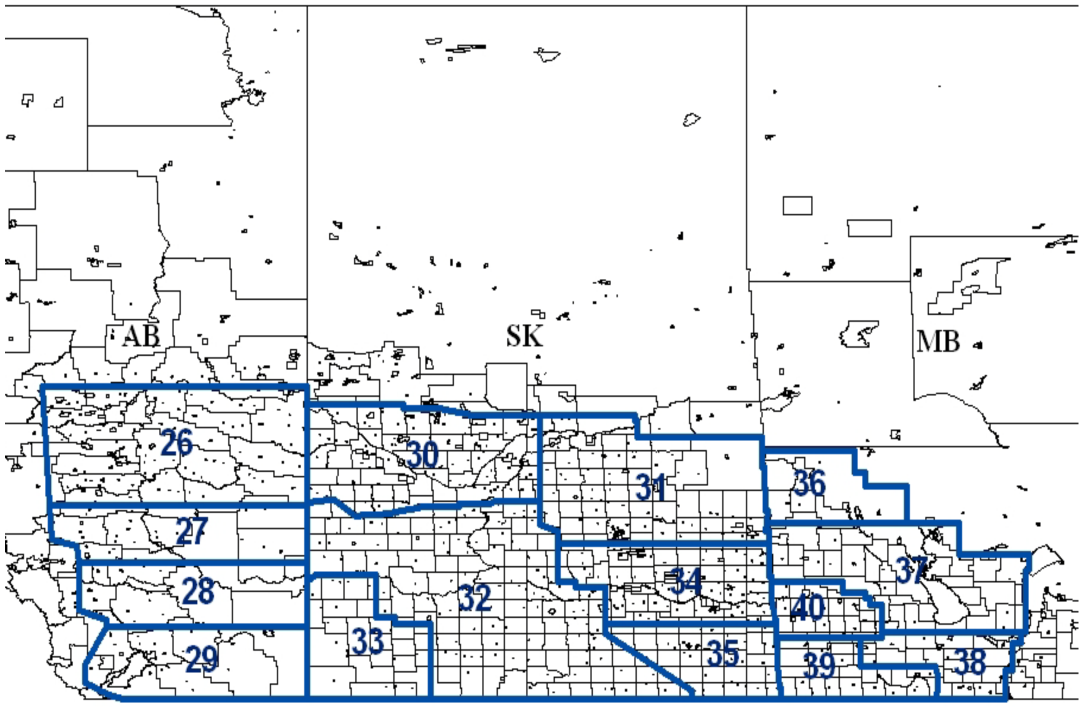

Figure 4: Strata of the Waterfowl Breeding Population and Habitat Survey (thick lines) and Census Consolidated Subdivision Boundaries of the Census of Agriculture (thin lines)

It is worthwhile examining the spatiotemporal variation of the agricultural variables to gain an understanding of the localized land use changes that have occurred since the 1960s. This is done in Figure 5. Although cropland intensification occurred variably across the PPR, increases are apparent for most regions, with the exception of the southeast corner of Alberta, the southwest corner of Saskatchewan, and parts of central Manitoba. The reasons are related to climate – southeast Alberta and southwest Saskatchewan are the most arid regions in the PPR – and geography, with the portion of central Manitoba showing no agricultural intensification containing large bodies of water. The proportion of cropland in the region increased roughly 22 percent points from 1961 to 2006.

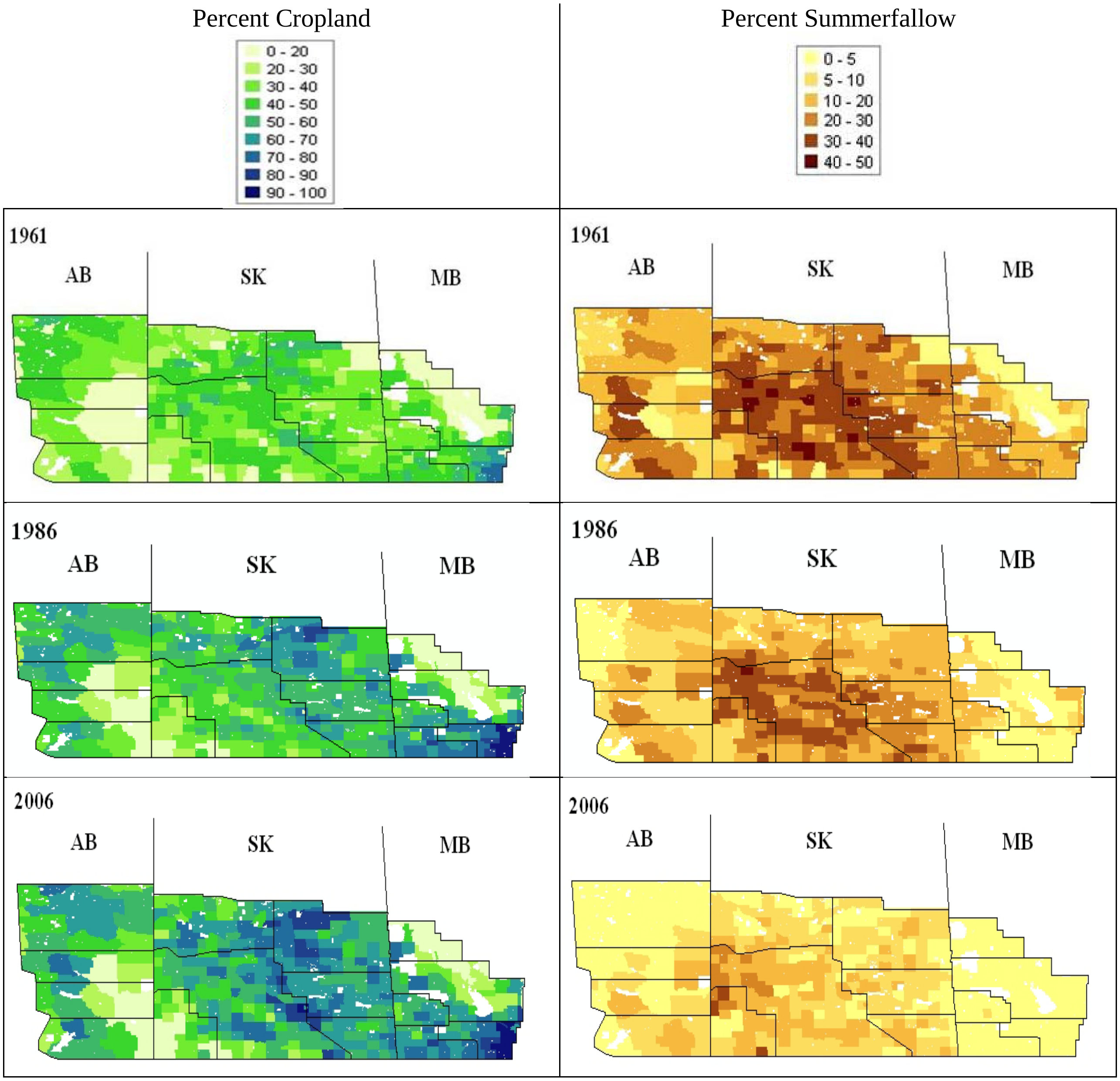

Figure 5: Spatiotemporal Variation of Percent Cropland and Percent Summerfallow

Summerfallow declined dramatically from a mean of 24% in 1961 to under 7% in 2006. Although not shown in Figure 5, the percent of improved pasture has not changed substantially. The mean increase is roughly 5%, so it could possibly be categorized as a slow moving variable.

Standardized Precipitation Index

The standardized precipitation index (SPI) is a drought index obtained from the North American Drought monitor; [2] it is available for various weather stations across the prairies. We employ data for the month of May from the weather station closest to the center of each survey region, selecting a short-term one month SPI as well as a longer-term 12 month index for our analysis. The index takes on values from -4 to +4: a value of zero indicates average wetness conditions as determined for the 1951-2001 standardizing period. Positive values indicate wet conditions, whereas negative values indicate dry conditions. We chose data from May to coincide with the month when planting generally occurs (and choice is made as to fallow or crop), and the month in which waterfowl breeding and habitat surveys are conducted.

4. Models and Estimation Methods

There are many advantages to using panel data. By examining data for a given number of regions over time, we can distinguish between inter- and intra-regional variability. Thus, we can construct richer models that are more informative than those that are available with pure cross-section or time series data. In addition, there are gains from additional degrees of freedom and the opportunity to control for omitted variable bias.

To examine the impact of agricultural land use on prairie waterfowl populations, three types of panel data models are considered: standard, dynamic and spatial. For each type of model, various specifications are compared and justifications for their use are provided. The three model specifications are provided in the remainder of this section.

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[2] http://www.ncdc.noaa.gov/temp-and-precip/drought/nadm/

4.1 Standard Panel Models

Fixed effects estimation is a standard approach in panel analysis. It is one way to model heterogeneity and potentially correct for omitted variable bias by controlling for unobserved time- and/or unit-invariant effects (Wooldridge 2010). Thus, it may be possible to obtain better estimates for the parameters of interest by allowing the model to account for the effects of variables that are too difficult to observe or for which data are not available (Wawro 2002). In the analysis, geographic and biological differences across strata likely affect the response of waterfowl to agricultural land use changes, leading to different responses across strata; this justifies a time-invariant cross-section effect. Similarly, there exist unit-invariant economic incentives, such as commodity prices, that potentially affect land use decisions and waterfowl abundance. Thus, the inclusion of a temporal fixed effect is justified theoretically. Statistically, *F*-tests support the inclusion of both temporal and unit fixed effects over pooled OLS. However, the fixed effects model essentially demeans the variables before applying OLS, making it unable to estimate the effects of observable variables of interest that are slow moving or time-invariant (Wilson and Butler 2007). Procedures outlined in Plümber and Troeger (2007) overcome this issue, but application of their technique is left for future research.

The unobserved effects can also be viewed as random draws from a probability distribution and estimated using random effects. However, whereas the unobserved effects may be correlated with the predictor variables with fixed effects models, they must be uncorrelated for the random effects estimator to be consistent. We are not convinced that the unobserved effects are orthogonal to the other covariates. In support of this view, we use a robust Hausman test (Schaffer and Stillman, 2010) to find that random effects estimation is inappropriate. Thus, we specify two fixed effects models:

$$\ln(y_{nt}) = x'_{nt}\beta + \alpha_n + \gamma_t + \varepsilon_{nt}, \varepsilon_{nt} \sim iid(0, \sigma_\varepsilon^2) \tag{1}$$

$$\ln(y_{nt}) = x'_{nt}\beta + \beta_6 lPND_{nt}CPL_{nt} + \beta_7 lPND_{nt}SMF_{nt} + \beta_8 lPND_{nt}PST_{nt} \\ + \alpha_n + \gamma_t + \nu_{nt}, \nu_{nt} \sim iid(0, \sigma_\nu^2) \tag{2}$$

where y_{nt} is duck density, measured as the number of ducks per square km, for stratum n in period t; n = 1 … 15; t = 1 … 10; $x'_{nt} = (lPND_{nt}, SPI_{nt}, CPL_{nt}, SMF_{nt}, PST_{nt})$ is a row vector of core explanatory variables that appear in every model; β is a 5 × 1 vector of coefficients; α_n is the unit effect; and γ_t is the period effect. The variables, their descriptions and expected signs are provided in Table 2.

Model (1) is the main effects model – a standard panel model with both unit- and time-specific effects. The fixed effects estimation procedure can be viewed as OLS on a transformed model in which the original variables have their group and time means subtracted and the overall mean added. This transformation essentially eliminates the fixed effects; thus, the estimation involves applying OLS to $D_{NT}y = D_{NT}X\beta + D_{NT}\varepsilon$, where

$$D_{NT} = I_{NT} - I_N \otimes \tfrac{1}{T}\iota_T\iota'_T - \tfrac{1}{N}\iota_N\iota'_N \otimes I_T + \tfrac{1}{NT}\iota_{NT}\iota'_{NT}$$

is the within projector, ι is a unit column vector with size denoted by its subscript and $\otimes$ denotes the Kronecker product.

The second model is the interactive effects model. Since habitat conditions are extremely important in the determination of waterfowl abundance, wetland numbers possibly influence or moderate the effect of the land use variables. Therefore, it is possible that the coefficients on the land use variables are different for different values of pond density. We test this hypothesis by including interactions between ponds and the land use variables.

Table 2: Independent Variables and the Expected Slope of Their Relationship with Waterfowl Density

Variable	Definition	Expected Slope
lPND	Natural log of pond counts per square kilometer	+
SPI	Either the 1-month or 12-month Standardized Precipitation Index	+
CPL	Percentage of farm area that is cropland	-
SMF	Percentage of farm area that is summerfallow	-
PST	Percentage of farm area that is improved pasture	-
CPL×lPND	Interaction term between CPL and lPND	+ or -
SMF×lPND	Interaction term between SMF and lPND	+ or -
PST×lPND	Interaction term between PST and lPND	+ or -
Fixed Effects	Unobserved cross-sectional or temporal controls	+ or -

4.2 Dynamic Panel Models

Allowing for heterogeneity by way of fixed or random effects is also an alternative, as well as a supplement, to dynamic models for modelling persistence in the data (Wawro 2002). Consequently, the next suite of models, motivated in part by Wilson and Butler (2007), examine dynamic panel models.

$$\ln(y_{nt}) = \alpha_n + \gamma_t + x'_{nt}\beta + \beta_6 ln(y_{nt-1}) + \varepsilon_{nt} \tag{3}$$

$$\ln(y_{nt}) = \alpha_n + \gamma_t + x'_{nt}\beta + \beta_6 lPND_{nt-1} + \nu_{nt} \tag{4}$$

$$\ln(y_{nt}) = \alpha_n + \gamma_t + x'_{nt}\beta + \upsilon_{nt}, \upsilon_{nt} = \rho\upsilon_{nt-5} + \xi_{nt} \tag{5}$$

Before proceeding with further explanations of these models, a clarification on notation is in order. As mentioned previously, there are 15 cross-sectional units and 10 temporal observations per unit; thus, each stratum has an observation every five years from 1961 to 2006, inclusive. However, we have access to annual waterfowl and wetland data, so the lags in (3) and (4) make use of this fact. Thus *t* = 1961, 1966 … 2006. For model 5, we subsequently refer to this process as a first-order autoregressive model.

Model 3 is the standard lagged dependant variable (LDV) model, which is theoretically justified since duck density in the previous period is a powerful predictor of duck density in the current period.[3] However, traditional OLS fixed effects estimation will be biased and inconsistent because the LDV is correlated with the transformed disturbance. A Wooldridge (2010, pp.319-320) test for autocorrelation yielded a p-value of 0.006; thus serial correlation is still present even with the addition of a LDV. One strategy for overcoming the estimation issues present with OLS is instrumental variables (IV), but finding suitable instruments is problematic. Choosing two lags of the dependent variable, which essentially exploits sequential moment restrictions (Wooldridge 2010), appears to be the standard approach; but, if the level of serial correlation is small, it may be better to use OLS instead of IV with weak instruments (Beck and Katz 1996). In addition, while IV yields consistent estimators, we only have ten time observations for each stratum, so the finite-sample properties of the IV estimator may be worse than under OLSNevertheless, both results are presented in the empirical results section.

Model 4 is the distributed lag (DL) model; model 5 is the first-order autoregressive (AR) model. Although the theoretical justification for model 3 is stronger than for model 4, which is stronger than model 5, comparisons of the estimates serve as a useful robustness check.

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[3] Year after year, female ducks generally return to the breeding grounds where they hatched, and male ducks follow their female partner (Baldassarre et al. 1994).

4.3 Spatial Panel Models

In controlling for unobserved unit heterogeneity, the models described previously account for regional characteristics but not spatial dependence or interaction. Of course, model misspecification potentially renders the estimators biased and inconsistent. Fortunately, spatial panel models can be specified to account for both unit heterogeneity, captured by pure fixed effects, as well as interactive heterogeneity, captured by the impact coefficients of the model (Debarsy and Ertur 2010). Maximum likelihood (ML) and generalized method of moments (GMM) are the most common methods used to estimate spatial models (Elhorst 2009) – we employ ML.

To account for spatial effects, two types of models are common: the spatial autoregressive model (SAR) and the spatial error model (SEM). The SAR model, also known as the spatial lag model, is typically used when the dependent variable for a given region is jointly determined with that of its neighbours, whereas the SEM model has a standard panel specification but views the error terms as correlated across space, and thus are non-spherical (Anselin et al. 2006). Moreover, both specifications can be combined to construct a higher-order spatial model (SARAR). For time period t, the SARAR specification is

$$Y_t = \rho W_N Y_t + X_t \beta + \alpha + \gamma_t \iota_N + \varepsilon_t, \text{ where } \varepsilon_t = \lambda M_N \varepsilon_t + \nu_t;\ \nu_t \sim N(0, \sigma_\nu^2 I_N), \qquad (6)$$

where Y_t is the $N \times 1$ lagged dependent variable, X_t is the $N \times 5$ matrix of explanatory variables, β is the 5×1 vector of coefficients, α is an $N \times 1$ vector of unit effects, γ_t is the scalar time effect, ι_N is a $N \times 1$ vector of ones, W and M are row-normalized spatial weight matrices, ρ is the spatial autoregressive coefficient, and λ is the spatial autocorrelation coefficient. In contrast to the aspatial models, the data are sorted first by time and then by spatial units – strata 26, 27, etc. for 1961 followed by strata 26, 27, etc. for 1966, and so on.

The spatial weight matrices, W and M, are positive, $N \times N$ and assumed to remain constant over time. They specify the strength and structure of the relationship between a region and its neighbours. The row elements represent the effect of all other regions on a particular stratum and the column elements represent the effect of a particular stratum on all other regions (Elhorst 2009). The choice of weight matrix is rather arbitrary; thus, we consider a Queen-based contiguity as well as an inverse distance matrix, both of which are common in the spatial econometrics literature. For Queen-based contiguity, all regions sharing a border or vertex are considered neighbours and the appropriate element is set to 1; all other elements are 0. For inverse distance, we use the inverse of the arc distance separating the strata centroids. Thus, all regions are neighbours, but the strength of the relationship is weaker for regions that are farther away. We do not allow for the possibility of self-influence; therefore, all diagonal elements are zero.

For computational reasons, the weighting matrices are row-standardized so that each row sums to 1. Finally, for stationarity, ${}^{1}/_{\omega_{min}} < \rho < {}^{1}/_{\omega_{max}}$ and ${}^{1}/_{\omega_{min}} < \lambda < {}^{1}/_{\omega_{max}}$, where ω_{min} and ω_{max} are the smallest and largest eigenvalues of the weight matrix. However, the smallest eigenvalue of a row-standardized weight matrix could be less than minus 1 (Elhorst 2009).

From (6), it is clear that the SAR and SEM models are special cases of the SARAR model in which λ or ρ is restricted to be zero, respectively. Following the procedures outlined in Anselin et al. (2006; hereafter ALJ), or Debarsy and Ertur (2010; hereafter DE), Lagrange multiplier (LM) tests can be constructed to determine the most appropriate specification. However, the procedure outlined in DE differs from ALJ with regard to the method adopted to demean the variables to eliminate the fixed effects. Recall that fixed effects estimation applies a within transformation to the variables; this method is also used by ALJ (2006). In contrast, DE follow a method outlined in Lee and Yu (2010; hereafter LY), who note that the traditional within transformation applied to SARAR models causes the maximum likelihood estimators (MLEs), including the MLE of the variance parameter, to be inconsistent unless N is large. More concerning is the bias of these estimators. The Monte Carlo results in LY show that the biases of the coefficient estimators for β are small regardless of which method is used to transform the data; however, the bias of the variance estimator is roughly 10 times larger using the standard within transformation when N and T are both small. This bias is potentially problematic for inference. Consequently, we obtained estimates for both types of transformed data and compare them in the next section.

The within transformation was described previously. Following DE, we refer to the LY method as a *pseudo*-within transformation. For simplicity, consider a SAR model with unit effects only: $Y_t = \rho W_N Y_t + X_t \beta + \alpha_n + V_t$, where $Y_t = [y_{1t}, y_{2t} \dots y_{Nt}]'$ is an $N \times 1$ vector, et cetera. The traditional within transformation uses the demeaning operator, $J_T = I_T - \frac{1}{T}\iota_T \iota_T'$, to remove the unit fixed effects. However, this operation creates linear dependence over the time dimension in the disturbances, and these are no longer well-behaved. To avoid this issue, LY use the eigenvectors of J_T to create an orthogonal transformation. The eigenvalues of J_T consist of one zero and T-1 ones. Let $F_{T,T-1}$ denote the $T \times (T-1)$ matrix of eigenvectors corresponding to the non-zero eigenvalues. The pseudo-within transformation for Y is

$$\begin{pmatrix} Y_{n,1}^* \\ \vdots \\ Y_{n,T-1}^* \end{pmatrix} = \left(F_{T,T-1}' \otimes I_N\right) \begin{pmatrix} Y_{n,1} \\ \vdots \\ Y_{n,T} \end{pmatrix},$$

which results in $Y_t^* = \rho W_N Y_t^* + X_t^* \beta + V_t^*$ when the transformation is applied to all variables. It follows that

$$E(V_n^* V_n^{*\prime}) = \begin{pmatrix} V_{n,1}^* \\ \vdots \\ V_{n,T-1}^* \end{pmatrix} \begin{pmatrix} V_{n,1}^* & \dots & V_{n,T-1}^* \end{pmatrix} = \sigma^2 \left(F_{T,T-1}' \otimes I_N\right)\left(F_{T,T-1} \otimes I_N\right) = \sigma^2 I_{N(T-1)}$$

and the log likelihood function, assuming normal errors, can be expressed as

$$LL(\beta, \rho, \sigma^2) = -\tfrac{N(T-1)}{2} \ln(2\pi\sigma^2) + (T-1)|S_n(\rho)| - \tfrac{1}{2\sigma^2} \textstyle\sum_{t=1}^{T-1} V_{nt}^{*\prime}(\beta, \rho) V_{nt}^*(\beta, \rho), \qquad (7)$$

where $S_n(\rho) = (I_N - \rho W_N)$ and $V_{nt}^* = S_n(\rho) Y_{nt}^* - X_{nt}^* \beta$. S_n is assumed to be invertible. In contrast, the log likelihood function for the direct approach is

$$LL^d(\beta, \rho, \sigma^2) = -\tfrac{NT}{2} \ln(2\pi\sigma^2) + T|S_n(\rho)| - \tfrac{1}{2\sigma^2} \textstyle\sum_{t=1}^{T-1} \tilde{V}_{nt}'(\beta, \rho) \tilde{V}_{nt}(\beta, \rho), \qquad (8)$$

where $S_n(\rho) = (I_N - \rho W_N)$, $\tilde{V}_{nt} = S_n(\rho) \tilde{Y}_{nt} - \tilde{X}_{nt} \beta$ and $\tilde{Y}_{nt} = Y_{nt} - \frac{1}{T} \sum_t Y_{nt}$, and $\tilde{X}_{nt} = X_{nt} - \frac{1}{T} \sum_t X_{nt}$ are time-demeaned variables.

When W_N is row-standardized, the corresponding transformed SAR model with two-way fixed effects is

$$\begin{aligned} Y_t^{**} = F_{N,N-1}' Y_t^* &= \rho\left(F_{N,N-1}' W_N F_{N,N-1}\right) F_{N,N-1}' Y_t^* + F_{N,N-1}' X_t^* \beta + F_{N,N-1}' V_{nt}^* \\ &= \rho(F_{N,N-1}' W_N F_{N,N-1}) Y_t^{**} + X_t^{**} \beta + V_{nt}^{**}. \end{aligned} \qquad (9)$$

Again, assuming normal errors, the log likelihood can be expressed as

$$LL(\beta, \rho, \sigma^2) = -\tfrac{(N-1)(T-1)}{2} \ln(2\pi\sigma^2) + (T-1)|S_n^*(\rho)| - \tfrac{1}{2\sigma^2} \textstyle\sum_{t=1}^{T-1} V_{nt}^{**\prime}(\beta, \rho) V_{nt}^{**}(\beta, \rho), \qquad (10)$$

where $S_n^*(\rho) = \left(I_{N-1} - \rho F'_{N,N-1} W_N F_{N,N-1}\right)$, $V_{nt}^{**} = S_n^*(\rho) Y_{nt}^{**} - X_{nt}^{**}\beta$, and $X_{nt}^{**} = F'_{N,N-1} X_{nt}^*$. (Complete derivations are provided by LY.) The corresponding likelihood function for the direct approach is

$$LL^d(\beta, \rho, \sigma^2) = -\tfrac{NT}{2}\ln(2\pi\sigma^2) + T|S_n(\rho)| - \tfrac{1}{2\sigma^2}\textstyle\sum_{t=1}^{T-1} \tilde{V}'_{nt}(\beta,\rho) J_N \tilde{V}_{nt}(\beta,\rho), \qquad (11)$$

where $J_N = I_N - \frac{1}{N}\iota_N \iota'_N$ is the deviation from group demean transformation and all other variables are defined in (8) above.

Table 3: Tests to Detect Spatial Effects

	Queen Contiguity		Inverse Distance	
	AE[a]	DE[b]	AE[a]	DE[b]
(1) LM_J	-	30.069	-	28.789
		(0.000)		(0.000)
(2) LM_ρ	27.470	19.571	22.864	15.969
	(0.000)	(0.000)	(0.000)	(0.000)
(3) LM_λ	27.918	29.812	22.136	28.467
	(0.000)	(0.000)	(0.000)	(0.000)
(4) $LM_{\lambda\mid\rho}$	1.070	0.065	0.235	0.416
	(0.301)	(0.799)	(0.628)	(0.519)
(5) $LM_{\rho\mid\lambda}$	0.621	105.108	0.963	96.70
	(0.431)	(0.000)	(0.327)	(0.000)
Chosen model	SAR or SEM	SAR	SAR or SEM	SAR
LR test for two-way effects	273.384	276.071	264.085	271.041
	(0.000)	(0.000)	(0.000)	(0.000)

Notes:
p-values are in parentheses. SAR refers to the spatial lag model; SEM refers to the spatial error model.
[a] Anselin et al. (2006) and Elhorst (2009) tests—standard within transformation.
[b] Debarsy and Ertur (2010) tests – Lee and Yu (2010) pseudo-within transformation.
(1) H_0: $\rho=\lambda=0$. (2) H_0: $\rho=0$. (3) H_0: $\lambda=0$. (4) H_0: $\lambda=0$, with ρ possibly different from 0.
(5) H_0: $\rho=0$, with λ possibly different from 0.

Now that the pseudo-within transformation has been outlined, we expand upon the previous LM tests. Anselin et al. (2006) extend into a spatial panel setting LM tests specified by Anselin et al. (1996) that test for a spatially lagged dependent variable and spatial autocorrelation in cross-sections. Elhorst (2009) also extends Anselin et al. (1996) by specifying robust LM tests that test for the presence of a spatial lag or spatial error term when the other is assumed to be present. DE test similar hypotheses, but the variables are transformed according to the LY (2010) method. We present the LM tests in Table 3; they indicate that spatial effects are relevant and that the specification should either be SAR or SEM, but not SARAR. Irrespective of the weight matrix, the DE tests support a SAR model whereas the ALJ tests are inconclusive. In addition, likelihood ratio (LR) tests for the significance of two-way fixed effects provide support for the inclusion of both unit and temporal effects. Lastly, similar to the standard panel specification, Hausman tests indicate that random effects estimation is not appropriate.

All spatial panel models were estimated using Matlab routines created by Elhorst (2009) and Debarsy and Ertur (2010).[4] The spatial weight matrices were created using ArcGIS. Because DE only consider unit-specific effects, we modified their code following the procedure outlined in LY (2010) to account for temporal effects as well. Monte Carlo simulations yield results similar to those presented in LY; thus, we assume our modifications are reasonably correct.

5. Empirical Results

Empirical results and various sensitivity tests are provided in this section. In

[4] The spatial econometrics toolbox is available at http://www.spatial-econometrics.com/.

general, the coefficient estimates have the expected signs and appear to be robust to various specifications and changes to the assumptions. Results are first presented for the static models, then the dynamic models and the spatial specifications.

5.1 Standard Panel Models

The coefficient estimates for each static model for the one-month and 12-month SPI drought indexes are presented in Table 4. Robust standard errors adjusted for clustering on stratum are reported as there is evidence of panel heteroskedasticity. As an example, the computed modified Wald statistic for group-wise heteroskedasticity (Baum 2001) for the main effects model with the one-month SPI is 82.83. The statistic is distributed χ^2_{15} under the homoskedasticity null with a 5% critical value of 25. Thus, we reject the null hypothesis. The computed statistics for the other model specifications are similarly large.

Using Pesaran's (2004) test for cross-sectional independence, we are unable to conclude that the panels are uncorrelated; thus, following Beck and Katz (1995), we also estimate panel corrected standard errors (PCSE). However, as they do not lead to different conclusions about the statistical significance of the land use variables, they are not reported.

For the main effects model with the one-month SPI, all land use regressors are significant at the 5% level. For cropland, a one percentage point increase is predicted to decrease duck density by 6%. For summerfallow, the predicted decrease is 7%, while it is 6% for pasture. With the 12-month SPI, the coefficient estimates and significance for cropland and summerfallow do not change substantially, but pasture becomes statistically and practically insignificant. As mentioned previously, pasture is a slow moving variable, so it is possible that this result is a statistical artefact or Type II error.

Table 4: The Effect of Agricultural Land Use on Duck Populations, Static Panel Models

	Main Effects		Interactive	
	1-Month SPI	12-Month SPI	1-Month SPI	12-Month SPI
lPND	0.450	0.398	0.507	0.390
	(0.084)***	(0.074)***	(0.201)**	(0.186)**
SPI	0.050	0.127	0.059	0.135
	(0.034)*	(0.028)***	(0.035)*	(0.026)***
CPL	-0.059	-0.050	-0.061	-0.053
	(0.029)**	(0.027)**	(0.033)**	(0.029)**
SMF	-0.074	-0.062	-0.079	-0.070
	(0.025)***	(0.023)**	(0.032)**	(0.030)**
PST	-0.061	-0.027	-0.050	-0.009
	(0.028)**	(0.030)	(0.041)	(0.043)
CPL×lPND			-0.001	-0.0007
			(0.003)	(0.003)
SMF×lPND			0.0003	0.0003
			(0.006)	(0.006)
PST×lPND			-0.004	-0.005
			(0.009)	(0.009)
Average Fixed Effect	4.782	4.391	4.884	4.589
	(1.179)***	(1.095)***	(1.350)***	(1.207)***

Notes: Robust standard errors adjusted for clustering on stratum reported in parentheses.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. Two-sided test for interaction terms and constant; one-sided test for all other coefficients.
All regressions employ 150 observations.

For the interactive models, the interaction terms are not significant, but that does not mean that there are no moderated relationships between land use and pond density. It is possible that an alternative functional form is more appropriate, and this product specification is only appropriate for detecting a bilinear relationship (Jaccard et al. 1990). As for the coefficient estimates on the predictor variables, they are not substantially different from the estimates from the main effects models. The negative effects of cropland and summerfallow are both strengthened, but the differences are less than one percentage point. Pasture is again insignificant.

5.2 Dynamic Panel Models

The coefficient estimates for each dynamic panel model for the one-month SPI are provided in Table 5. The estimates for the 12-month SPI are not provided, but changes in the coefficients generally mirror what occurred with the static models; pasture becomes insignificant, and the estimates for cropland and summerfallow are strengthened, but not substantially. In addition, we do not present empirical results for models with interaction terms as these are statistically insignificant in all models. When comparing the estimates, we follow Wilson and Butler (2007) and refer to a result as strengthened or weakened if the estimate changes in magnitude by more than half a standard error, as measured by the standard error of the benchmark.

Table 5: The Effect of Agricultural Land Use on Duck Populations, Dynamic Panel Models

	Model				
	(3) FE[a]	(3) IV[b]	(4) DL	(5) AR	PCSE[c]
lPND	0.478	0.487	0.449	0.494	0.450
	(0.085)***	(0.072)***	(0.086)***	(0.082)***	(0.105)***
SPI-1 Mo.	0.003	-0.013	0.047	0.066	0.050
	(0.024)	(0.037)	(0.033)*	(0.034)**	(0.039)
CPL	-0.049	-0.046	-0.058	-0.030	-0.059
	(0.018)***	(0.019)***	(0.027)**	(0.022)*	(0.024)***
SMF	-0.054	-0.047	-0.074	-0.069	-0.075
	(0.016)***	(0.020)***	(0.024)***	(0.021)***	(0.022)***
PST	-0.050	-0.046	-0.060	-0.054	-0.061
	(0.022)**	(0.027)**	(0.030)**	(0.030)**	(0.033)**
$Ln(D_{t-1})$	0.461	0.616			
	(0.118)***	(0.174)***			
$lPND_{t-1}$			0.062		
			(0.129)		
Average	3.015	2.420	4.685	3.439	6.583
Fixed Effect	(0.745)***	(1.034)***	(1.043)***	(1.058)***	(1.029)***
$\hat{\rho}$[d]				-0.043	-0.011

Notes: Regression (5) employs 135 observations; all others use 150 observations.
[a] Fixed effects estimator. Robust standard errors adjusted for clustering on stratum reported in parentheses.
[b] Instrumental variables with $\ln(D_{it-2})$ to instrument $\ln(D_{it-1})$.
[c] Prais-Winsten regression, common first-order autocorrelation. Correlated panels corrected standard errors, normalized by the number of observations, reported in parentheses.
[d] Estimated coefficient of the AR(1) process.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. Two-sided test for the constant; one-sided test for all other coefficients.

The coefficient estimates for the land use variables are similar across models, and statistical significance is maintained across all model specifications. In addition, the estimates generally remain practically significant. A Hausman test comparing the IV and OLS estimates produced a test statistic of 1.32. The statistic is distributed χ^2_6 under the null with a 5% critical value of 12.59; therefore, we conclude that the differences between the OLS and IV estimates are not systematic. This result is likely because the level of serial correlation is small. The estimates of the serial correlation coefficient produced by the (5) AR model and PCSE are -0.043 and -0.011, respectively. Moreover, regardless of whether equation (3) is estimated by OLS or IV, the coefficient estimate on the LDV is not near one, so there is likely little concern over unit roots and cointegration.

For cropland, the most significant difference in Table 5 occurs between (5) AR and PCSE—the (5) AR estimates are half those of PCSE. For summerfallow and pasture, the most significant difference occurs between (3) IV and PCSE—PCSE results are strengthened by 2.8 percentage points for summerfallow and 1.5 percentage points for pasture.

Compared to (1), (3) has weaker results as expected, because the effects of the other covariates should diminish when past realizations of the dependent variable are used as regressors. Also compared to (1), the results of (4) DL and PCSE remain unchanged, but for (5) AR, the results weaken for cropland only. Thus, the estimates from (1) are relatively robust.

5.3 Spatial Panel Models

As discussed previously, LM tests indicate that the most appropriate model either contains a spatially lagged dependent variable or a spatial autoregressive process in the error. Support for the SAR model is somewhat stronger than the SEM specification, especially since Jarque-Bera tests suggest that residuals under the direct approach are not normally distributed, thereby calling into question the reliability of the Anselin et al. (2006) and Elhorst (2009) LM tests. Nevertheless, for comparison, estimates for both models are reported in Table 6. Further, Lee and Yu (2010) point out that the usual MLEs are inconsistent for SAR models. When these models include both fixed unit and time effects, none of the parameters are estimated consistently unless there are a large number of cross sections. Moreover, the estimators are biased even when N and T are large; therefore, as an alternative to implementing a bias-correction procedure, LY (2010) proposed a data transformation approach that yields consistent estimators as long as either N or T is large. Although neither N nor T is considered large in this study, Monte Carlo experiments suggest that in comparison to the direct ML approach, the LY approach has more desirable finite sample properties.

Both estimation methods are presented in Table 6. For the SAR model, the direct and transformation approaches produced virtually identical estimates of β. Other than different estimates obtained for ρ and σ^2, the only notable difference is the coefficient estimate for PST. With inverse distance as the spatial weight matrix, PST is not significant under the LY approach, whereas it is significant at the 10% level under the direct approach. Again, this is likely an issue with including time-invariant effects whilst also trying to model a slow moving variable. Interestingly, the coefficient estimates for the land use variables appear to be influenced more by the weight matrix than the estimation approach, whereas the strength of the spatial autocorrelation is influenced more by the estimation approach.

Table 6: The Effect of Agricultural Land Use on Duck Populations, Spatial Panel Models

	Queen Contiguity		Inverse Distance	
SAR Model:	Direct[a]	LY[b]	Direct[a]	LY[b]
lPND	0.412	0.400	0.415	0.398
	(0.063)***	(0.068)***	(0.065)***	(0.071)***
SPI	0.031	0.025	0.032	0.022
	(0.028)	(0.030)	(0.029)	(0.031)
CPL	-0.049	-0.045	-0.054	-0.052
	(0.016)***	(0.017)***	(0.016)***	(0.018)***
SMF	-0.059	-0.055	-0.066	-0.061
	(0.016)***	(0.017)***	(0.016)***	(0.017)***
PST	-0.056	-0.055	-0.039	-0.029
	(0.023)***	(0.025)**	(0.024)*	(0.026)
ρ	0.457	0.599	0.461	0.681
	(0.072)***	(0.084)***	(0.085)***	(0.103)***
σ^2	0.0576	0.0663	0.0616	0.0710
Jarque-Bera[c]	12.025	0.475	11.364	0.224
	(0.002)	(0.789)	(0.003)	(0.894)
SEM Model:				
lPND	0.480	0.449	0.475	0.444
	(0.066)***	(0.076)***	(0.070)***	(0.076)***
SPI	0.036	0.051	0.040	0.052
	(0.030)	(0.035)*	(0.032)*	(0.035)*
CPL	-0.045	-0.060	-0.059	-0.059
	(0.015)***	(0.020)***	(0.016)***	(0.020)***
SMF	-0.053	-0.076	-0.068	-0.078
	(0.016)***	(0.019)***	(0.017)***	(0.020)***
PST	-0.068	-0.060	-0.054	-0.062
	(0.027)***	(0.028)**	(0.027)**	(0.028)**
λ	0.548	-0.044	0.540	-0.287
	(0.072)***	(0.138)	(0.083)***	(0.194)
σ^2	0.0540	0.0894	0.0593	0.0997
Jarque-Bera[c]	6.294	0.494	4.574	0.414
	(0.043)	(0.781)	(0.102)	(0.813)

Notes: Except where noted, standard errors are in parentheses.

[a] Direct maximum likelihood in which the common parameters and fixed effects are jointly estimated.

[b] Lee and Yu (2010) data transformation with quasi-maximum likelihood estimation.

[c] p-values are in parentheses.

*** Significant at 1%, ** Significant at 5%, * Significant at 10%. Two-sided test for ρ and λ; one-sided test for all other coefficients.

The coefficient estimates for the SEM model are also very similar to the other models that have been discussed. The DE (2010) LM tests indicated that the SEM model was inappropriate, so unsurprisingly, λ is insignificant when the LY (2010) transformation is applied to the data and the coefficient estimates are virtually identical to model (1), the standard panel model.

A brief examination of the estimates in Table 6 shows that results are on par with what has already been presented for the standard and dynamic panel models. However, interpreting the coefficients as marginal effects neglects the simultaneous feedback characteristic of the SAR model and any potential indirect effects (LeSage and Pace 2009a). Recall that the SAR specification is

$$Y_t = \rho W_N Y_t + \beta_1 lPND_t + \beta_2 SPI_t + \beta_3 CPL_t + \beta_4 SMF_t + \beta_5 PST_t + \alpha + \gamma_t \iota_N + \varepsilon_{it}. \quad (9)$$

Any spillover effects can be obtained by expressing (9) in its reduced form:

$$\begin{aligned} Y_t = {} & (I_N - \rho W)^{-1}\beta_1 lPND_t + (I_N - \rho W)^{-1}\beta_2 SPI_t + (I_N - \rho W)^{-1}\beta_3 CPL_t + \\ & (I_N - \rho W)^{-1}\beta_4 SMF_t + (I_N - \rho W)^{-1}\beta_5 PST_t + (I_N - \rho W)^{-1}(\alpha + \gamma_t \iota_N) + \\ & (I_N - \rho W)^{-1}\varepsilon_{it.}. \end{aligned} \quad (10)$$

By deriving the matrix of partial derivatives of Y_t with respect to the land use variables, we can determine the direct and indirect effects of agricultural land use changes on waterfowl populations:

$$\frac{\partial Y_t}{\partial CPL_t} = (I_N - \rho W)^{-1}\beta_3, \frac{\partial Y_t}{\partial SMF_t} = (I_N - \rho W)^{-1}\beta_4 \text{ and } \frac{\partial Y_t}{\partial PST_t} = (I_N - \rho W)^{-1}\beta_5 \quad (11)$$

The diagonal elements of these matrices are the direct effects, whereas the off-diagonal elements are indirect effects (DE 2010). Using summary measures from LeSage and Pace (2009a, b), we can calculate an average total impact, an average direct impact and an average indirect impact. These measures and their associated *t*-statistics are presented in Table 7. Empirically simulated values of ρ and β can be used to generate empirical distributions for the impact measures (see LeSage and Pace 2009a); the *t*-statistics are based on 10,000 sampled raw parameter estimates of the SAR model.

The average total impact for each variable is derived by averaging the row-sums of the appropriate matrix in (11). The average direct impact is obtained by taking the average of the diagonal elements. Then, the indirect impact is the difference between the total and direct impacts or the average of the row-sums of the off-diagonal elements.

Table 7: Impact Measures

	Queen Contiguity					
	Direct			LY		
	CPL	SMF	PST	CPL	SMF	PST
Direct	-0.0520	-0.0634	-0.0600	-0.0518	-0.0624	-0.0624
	(-3.054)***	(-3.757)***	(-2.410)***	(-2.625)***	(-3.130)***	(-2.113)**
Indirect	-0.0374	-0.0457	-0.0432	-0.0610	-0.0735	-0.0736
	(-2.143)**	(-2.371)***	(-1.843)**	(-1.587)*	(-1.483)*	(-1.306)*
Total	-0.0894	-0.1091	-0.1031	-0.1129	-0.1360	-0.1360
	(-2.746)***	(-3.245)***	(-2.230)**	(-2.056) **	(-2.100)**	(-1.674)**
	Inverse Distance					
	Direct			LY		
	CPL	SMF	PST	CPL	SMF	PST
Direct	-0.0571	-0.0690	-0.0413	-0.0604	-0.0713	-0.0337
	(-3.278)***	(-4.010)***	(-1.623)*	(-1.829)**	(-2.017)**	(-0.941)
Indirect	-0.0436	-0.0527	-0.0315	-0.1024	-0.1209	-0.0572
	(-2.014)**	(-2.169)**	(-1.296)*	(-0.293)	(-0.306)	(-0.240)
Total	-0.1006	-0.1216	-0.0728	-0.1627	-0.1923	-0.0909
	(-2.786)***	(-3.217)***	(-1.517)*	(-0.431)	(-0.451)	(-0.344)

Notes: *t*-statistics in parentheses are based on 10,000 sampled raw parameter estimates of the SAR model.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%.

To explain the interpretation of the impact measures, we consider the impact measures for CPL for the direct ML approach with Queen contiguity spatial weights. From

Table 7, the average direct impact of a 1 percentage point increase in cropped land (CPL) on duck density is -5.2 percent. The corresponding coefficient estimate from Table 6 is -4.9 percent. The difference of -0.03 percent represents the feedback effects that return after passing through neighbouring strata. Since this difference is small, it is unlikely to be of practical significance.

The indirect impacts are also considered spatial spillovers (LeSage and Pace, 2009a). They can be interpreted as the impact on a typical stratum if CPL throughout the entire PPR increased by one percentage point. Since the indirect impact for CPL is negative, this indicates that duck density in a typical stratum would decrease by 3.7%. All else equal, the indirect impacts are larger using an inverse distance weight matrix because there are more neighbours. Additionally, the magnitude of the spatial autocorrelation coefficient ρ is much larger using the Lee and Yu (2010) transformation; consequently, the average indirect impacts are also much larger. It is a mistake, however, to interpret the magnitude and significance of ρ as representing spatial spillover effects. For example, the indirect impacts of the LY approach with an inverse distance matrix are not significantly different from zero whereas ρ is significant. If we interpret ρ as the spatial spillover effect, we would incorrectly infer that the agricultural variables exert larger negative impacts on duck density.

6. Conclusions

The aim of this study was to determine the impact of agricultural land use changes on waterfowl abundance in the Canadian Prairie Pothole Region. Recognizing that empirical results and conclusions are highly contingent on the strategies and methods used to obtain them, various static, dynamic and spatial panel model specifications were examined to ascertain the robustness of empirical results. In general, the conclusions hold up fairly well. The main static model finds that a one percentage point increase in the percentage of farm area that is cropland is predicted to decrease the number of ducks per square km by 6%, while the respective declines for summerfallow and pasture acreage are 7% and 6%. The estimates from dynamic specifications are more conservative. For the lagged dependent variable model, a one percentage point increase in cropland is predicted to decrease duck density by 4.6%. For summerfallow and pasture, the predicted decreases are 4.7% and 4.6%, respectively. Spatial autoregressive models allow the derivation of measures for assessing direct and indirect impacts. The estimated direct impacts fall between the estimates obtained from the standard and dynamic models, but when spillover effects are also included the estimated impacts exceed those predicted by the standard or static model.

The results suggest that, when wetlands are lost at one location, ducks do not compensate by breeding in other locations, or, if they do, that there is an overall reduction in fecundity. On the other hand, this makes programs to retain or create wetlands all the more worthwhile because additional wetlands in one location will result in enhanced productivity of ducks in another. It would appear that there are economies of scale for waterfowl in wetlands provision.

Because geographically referenced data are used to answer the research question, it is most logical to use a spatial model to conduct the analysis. In this particular case, the bias resulting from not explicitly modelling spatial dependencies may not be practically significant, but neglecting possible indirect impacts only gives researchers a partial picture of how agricultural land use changes affect waterfowl populations. For example, one spatial model estimates that the direct impact of a one percentage point increase in cropland will result in a 5% decline in duck density for a typical stratum, although the total impact is much larger (9%) because land use changes in one region not only affect the waterfowl population for that stratum, but also impact the population in surrounding regions. Thus, both standard and dynamic panel models yield downward biased estimators.

As a secondary goal, we sought to test whether wetland abundance moderated the effects of agricultural land use variables, but found no statistically significant bilinear relationship. Research exploring different functional forms is left to future analyses.

One possible application for the results of this study is the assessment of the efficiency of conservation programs. As a crude illustration, consider the $1.2 billion that the North American Waterfowl Management Plan has spent from 1986-2008 to secure 25,500 km^2 of land in the Canadian Prairie Pothole Region. Simply averaging over this 23 year period, we determine that 1,100 km^2 of farmland was secured annually at a cost of $52 million. In 2006, 1,100 km^2 constituted 0.25% of farm area and waterfowl density was roughly 30 ducks per square km. The conservation dollars spent securing habitat to increase the waterfowl population by a single duck can be estimated using these figures and the results from the various models. These calculations are presented in Table 8. For further simplicity, we assume that the 1,100 km^2 of secured land came entirely from cropland. In that case, the estimates range from $107 to $262 per duck, although these estimates are on the high side because land taken from summerfallow or pasture to be maintained as wetlands would be less costly to secure.

Nonetheless, the empirical results indicate that, when determining the benefits of conserving wetlands, biologists need to look beyond the impact on nearby duck numbers and measure population increases in neighboring strata as well. By considering these indirect or spillover impacts of wetlands protection, the costs of preventing declines in waterfowl numbers or enhancing populations are also lower.

Table 8: Estimates of Conservation Dollars Spent Per Duck in 2006

	Standard[a]	Dynamic[b]	Spatial A[c]	Spatial B[d]
Δ Duck Density	+0.44	+0.35	+0.67	+0.85
Δ Ducks in PPR	254,438	198,375	385,538	486,881
Expenditure per Duck	$204	$262	$135	$107

Notes: The Canadian Prairie Pothole Region is roughly 575,000 km^2.
[a] Model (1), standard panel specification without interaction effects.
[b] Model (3), lagged dependent variable model estimated by IV.
[c] Model (9), spatial lag model using a Queen contiguity weight matrix and demeaned data.
[d] Model (9), spatial lag model using a Queen contiguity weight matrix and data transformed according to the Lee and Yu (2010) method.

Admittedly, the models employed in this study were not overly complex. For example, higher-order dynamic processes were not examined and hierarchical models were not explored. More importantly, the spatial unit chosen for this analysis was not ideal. Given that waterfowl data are available at the transect level and agricultural data are available for census consolidated subdivisions, it would be more interesting to examine spatial interactions at a finer spatial resolution.[5] Therefore, there is room to incorporate these aspects into future analyses to provide stronger inferences about the impact of anthropogenic activity on waterfowl populations.

[5] The locations of transects are provided in Figure 1. See also USFWS (2010a, p.60).

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