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RESEARCH ARTICLE

The United States–China Trade War and Impact on the Post-Conservation Reserve Program Land Allocation

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Abstract
We use a Bayesian approach to estimate elasticities of former Conservation Reserve Program (CRP) land allocation and the impact of the US–China trade conflict on post-CRP land transitions. Economically acceptable elasticities of land exiting CRP are important for applied analysis, including market shocks and environmental policy. Taking as given the total area exiting the CRP, the Phase 1 deal raised the posterior mean of national post-CRP soybean area by 155 thousand acres and the market facilitation program by 89 thousand acres. Cross-commodity effects are important, and elasticities vary depending on the direction and magnitude of changes in net returns and payments.

Keywords: agricultural policy; Bayesian inference; bilateral trade dispute; CRP contract expiration; elasticity of post-CRP land transition; zero-adjusted Dirichlet regression

JEL classifications: Q24; Q18

1. Introduction

A trade dispute between the USA and China affected commodity markets and prices, with possible consequences for land use. On July 6, 2018, China enacted retaliatory import tariffs on US food and agricultural products, including soybeans (U.S. Department of Agriculture, Foreign Agricultural Service (USDA-FAS), 2018). China's response included 25% retaliatory tariffs on soybean imports from the USA (American Farm Bureau Federation (FB), 2018a). China subsequently pledged to increase imports of agricultural commodities from the USA in 2020 and 2021 under the US–China Economic and Trade Agreement (Phase 1 deal) signed on January 15, 2020.

The trade dispute reduced and reoriented US soybean exports. Taheripour and Tyner (2018) estimated that the retaliatory tariffs reduced China's imports of US soybeans by 17.0–32.6 million metric tons (MMT), while total US soybean exports decreased by 14.0–20.0 MMT relative to the base year of 2016. Subsequent direct trade loss estimation implied \$10.7 billion loss of soybeans trade due to the retaliatory action from China over 2 years from 2018 (Grant et al., 2021). Although China accounted for 62.3% of total US soybean exports in 2016, lost sales to China were partially offset by an increase in the soybean exports to the European Union (EU) and the rest of the world (USDA-FAS, 2020). Food and Agricultural Policy Research Institute and Agricultural Markets and Policy (FAPRI AMAP, 2020) also saw the US impact of the trade war mitigated by increasing imports by the EU, Japan, and the rest of the world.

Cropland-use decisions are driven by relative returns, and the US commodity prices were also affected by the bilateral trade dispute. Previous studies estimated a 2.0–5.0% reduction in the soybean price because of the bilateral trade war (Li et al., 2018; Taheripour and Tyner, 2018). Zheng et al. (2018) indicated that US domestic prices for cotton and sorghum decreased by 1.2 and

10.6%, respectively, using a multinational partial equilibrium model. FAPRI (2020) analysis of the Phase 1 deal projected that the US soybean producer price was 4.3% higher in the 2020/2021 marketing year relative to the price if trade friction continued.

Payments can also influence land-use decisions, and certain commodity price impacts of tariffs on farm income were to be offset by the Market Facilitation Program (MFP). The 2018 MFP made payments of $1.65 per bushel of soybeans harvested (U.S. Department of Agriculture, Office of Cheif Economist (USDA-OCE), 2018) with smaller payments for several other commodities. Giri et al. (2018) estimated that soybean producers in Arkansas and Illinois received $24 and $31 per acre more than they would have if there had been no retaliatory tariffs and no MFP payments. The second round of MFP payments in 2019 used different criteria. Producers received a payment rate per acre planted to qualifying crops, with payment rates differing by county but not by commodity produced on a particular farm. Since farmers had to grow a crop to qualify for the payment, the MFP may have affected land use, including the use of environmentally sensitive land coming out of CRP.

The end of the trade dispute could also affect land use in general and CRP land use in particular. The Phase 1 deal between the two nations was expected to create upward pressure on soybean prices, and observed prices rose in the final months of 2020 and early 2021 because of the Phase 1 agreement and other factors (FAPRI, 2021).

Change in price and corresponding payment due to the trade war affects the post-CRP land-use transition. For example, low US producer prices encourage the renewal of existing CRP contracts, the allocation of new land to CRP, or land exiting CRP to go to noncrop uses such as forest, pasture, and range. If prices are high enough to create high returns compared to the CRP payment, half of land exiting the program would not be re-enrolled according to surveys conducted before the first CRP contract expiration (Johnson et al., 1997; Osborn et al., 1995; Skaggs et al., 1994; Cooper and Osborn, 1998). Previous studies estimated the sensitivity of post-CRP land transition with respect to expected net returns of agricultural activities based on actual CRP land use decisions after starting the expiration. For example, Roberts and Lubowski (2007) and Sullivan et al. (2004) found that a one-half increase in expected net return led to an estimated 8.2–13.1% change in the area returning to crop production after exiting CRP in 1996, the first year that contracts expired. These results imply an elasticity of 0.16–0.26.

These studies also found that the cross-return sensitivity is more inelastic as, for example, the elasticity of post-CRP land going to crop production with respect to pasture returns was −0.03 to −0.10.

The primary research objectives of this paper are to estimate elasticities of post-CRP land use and examine the relationship between the US–China trade war and changes in post-CRP land use. These elasticities represent important contributions that help scientists understand the sensitivity of CRP impacts on crop supplies and environmental outcomes after contracts expire. Moreover, relative to results published in previous articles, the elasticities provided here are based on more data that has become available as additional land has come out of CRP. Finally, this study estimates the allocation of land leaving the CRP program, focusing on how the price effects and payments affected land going back into corn, soybeans, wheat, and other crops relative to forest, pasture or range, and other uses. The seven agricultural land-use categories include corn, soybeans, wheat, other crops, pasture/range, forest, and other land-use activities. Changes in post-CRP land use occur due to fluctuations in expected net returns, including the price impacts of the bilateral trade dispute and the Phase 1 deal, as well as MFP payments. Therefore, we prepare a base case and two alternative scenarios for the analysis.

The study treats total acres exiting the CRP as exogenous over scenarios. Thus, the changes we estimate do not consider the possible bilateral trade war impact on the decisions to re-enroll in the CRP when contracts expire, nor does it consider impacts on new CRP enrollment. To do this, a zero-adjusted Dirichlet regression (ZADR) model (Tsagris and Stewart, 2018) is estimated.

Data from the National Resource Inventory (NRI) survey are used because they represent land parcels returning to specific land-use activities when CRP contracts expire. The model uses those observations to estimate the proportion of land devoted to particular uses after exiting the CRP as a function of expected returns to the uses.

A critical contribution of this paper is an estimation of post-CRP land-use elasticities that govern the transition to crop production and other uses. Compared to the existing literature, our study provides a novel measure of the land-use transition for each agricultural region in the contiguous USA. Furthermore, the results will enhance the accuracy of estimating the impact on CRP environmental benefits because the land-use transition to specific crop production has an idiosyncratic change in ecosystem service (Houghton and Nassikas, 2017; Jansson et al., 2021; Mathew et al., 2017). We apply these estimates to the US–China trade dispute and the Phase 1 trade agreement to demonstrate the value. Results show how our estimated elasticities relate to applied land-use analysis.

2. Economic Framework

The bilateral trade dispute yields a spillover effect upon land-use decisions due to crop price changes and associated subsidies. The adverse price shocks reduce net returns to crop production compared to other land uses. In a dynamic land-use model with specific assumptions, i.e., risk-neutral landowner, homogeneous land quality, no spatial correlation, constant marginal conversion cost, and independence of land parcel size to relative profitability for other land-use alternatives, a land manager compares expected net returns after extracting the variable conversion cost of all possible alternative land-use options, including the annual CRP payments in case of re-enrollment (Roberts and Lubowski, 2007). As a result of optimization, the land-use activity with the highest expected net return minus conversion cost will be chosen by a landowner.

Let net profit of a land use alternative equal the return less the conversion cost at a specific time. It is assumed to be a linear combination of explanatory factors and an error term, which includes all composite unobserved factors. As theory indicates, the probability of returning to a land-use activity after leaving the CRP contract is the likelihood that the difference in profits between one and another activity whose profit is the highest among others is greater than zero. In other words, the difference in error terms should be less than the difference between explained linear combinations of the two. The distribution followed by the difference of the error terms determines the probability. Probit-type models can estimate the probability and its determinants if it follows the normal distribution. Otherwise, the assumption of a Gumbel distribution allows researchers to employ logit-type models. Many studies (Lubowski et al., 2008; Roberts and Lubowski, 2007; Skaggs et al., 1994; Sullivan et al., 2004, pp. 85–95) employed land parcel data to analyze the probability of land-use transitions based on probit- and logit-type models, while others use county, state, or regional land-use shares to study it (Isik and Yang, 2004; Parks and Kramer, 1995; Parks and Schorr, 1997). Even though empirical analysis often uses aggregate data with logit or probit models, such aggregate data can make it challenging to satisfy statistical fitness, so county-level or even smaller geography units might be preferred (Parks and Kramer, 1995, p. 233).

Moreover, using proportions of land acres to approximate the probability has to be transformed by a nonlinear function such as logit (Isik and Yang, 2004, p. 248). Therefore, the estimated coefficient parameters have explaining power in terms of the mean of transformed response but not the mean of the original dependent variable. Given Jensen's Inequality, the average of the transformed response is not equal to the transformed average of the original response, so it is not similar to the back-transformed estimated response. The difference between the two implies that the interpretation of parameters under the original scale could create the bias (Cribari-Neto and Zeileis, 2010; Douma and Weedon, 2019).

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3. Data

We use USDA NRI survey data to obtain the ratio of CRP land left from the program to CRP land expiring. The NRI is the land parcel survey estimating land-use or land-cover changes across the nation every 5 years (U.S. Department of Agriculture, Natural Resources Conservation Service (USDA-NRCS), 2020).

The survey can identify acres now in use for different activities but was under the CRP contract 5 years ago, since the survey includes CRP questions to understand each sample point's contract and conservation practice status from 1992 (USDA-NRCS, 2016). Although the individual observations are not publicly available, scholars can access the aggregated data. The acres in land-use/land-cover transition from CRP to other activities are aggregated by the USDA Farm Production Region (FPR). FPR consists of seven regions: Corn Belt and Lake States, Mountain, Northeast, Northern Plains, Pacific, Southeast, and Southern Plains. Data represent seven possible land-use categories employed by the NRI survey: corn, soybeans, wheat, other crops,[1] pasture/range, forest, and other activities. Since the data are quinquennial from 1992 to 2017, the sample size is 35 or five observations for each of the seven FPRs. As the survey does not track the reason for exit, the data contain all possible exiting cases, including contract expiration, early release, and termination from the program. The data can be transformed into the proportion of acres returned to each of the possible land-use activities with respect to the total acres that exited the CRP contract, denoted by the post-CRP land-use share, as follows:

$$y_{ijt} = \frac{\text{Area returning to the activity } j \text{ in region } i \text{ in period } t}{\text{Total area that exited CRP in region } i \text{ in period } t} \tag{1}$$

where the subscript $i = \{1, \ldots, 7\}$ denotes the FPR. Descriptive statistics of post-CRP land-use share imply that minimum values are zeros except for other crops and pasture/range in Table 1. Also, the samples have long right tails as Fisher–Pearson's coefficients are positive from 0.59 to 2.81. The skewness indicates that the standard statistical approaches are not likely to fit the analysis due to violating the normality and constant variance assumptions of error terms (Cribari-Neto and Zeileis, 2010; Douma and Weedon, 2019). Moreover, the zero observations rules out the simple Dirichlet regression model because it only applies to the proportional variable without zero and one values (Liu and Kong, 2015; Tsagris and Stewart, 2018). Therefore, the ZADR model is suitable for the post-CRP land-use analysis.

Each post-CRP land-use share is a function of the 5-year average of the own expected net return and absolute differences in average expected net returns between own and other land-use alternatives. Calculating the quinquennial averages of the expected net returns follows the approach introduced by Roberts and Lubowski (2007) and uses different data sources. The process of calculating net returns is either the total revenues multiplied by the revenue–cost ratios or the subtraction of operating costs from the total revenue. The total revenues consist of market revenue and government payment.

For crop production categories, market revenues are the product of prices received and yield per acre divided by acres planted, obtained from the Quick Stats database (U.S. Department of Agriculture, National Agricultural Statistics Service (USDA-NASS) (2020)). The FAPRI and AMAP (2021), an intermediate source that tracks USDA or other official data, provided government payments per acre planted. The pasture/range revenue uses the non-alfalfa hay price received (USDA-NASS, 2020) as a proxy for forage value. Because the pasture/range yields correspond to the soil components in each county, USDA-NRCS (2018) provides yields per each soil component converted those units to short tons from animal units per month (Pratt and Rasmussen, 2001). The revenue from timber production is defined as the component of the

[1]The other crops category includes barley, cotton, edible dry beans, hay, oats, peanuts, rice, sorghum, sugar beets, sugarcane, and sunflower.

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Table 1. Descriptive statistics ($N = 35$)

Variable	Activity	Statistics					
		Mean	S.D.	Min.	Median	Max.	Skewness
[Dependent] Post-CRP land-use share	Corn	0.09	0.10	0.00	0.05	0.32	1.26
	Soybeans	0.08	0.10	0.00	0.02	0.34	1.34
	Wheat	0.13	0.13	0.00	0.08	0.52	1.69
	Other crops	0.27	0.16	0.06	0.27	0.62	0.59
	Pasture/Range	0.35	0.20	0.04	0.30	0.83	0.73
	Forest	0.08	0.20	0.00	0.00	0.71	2.37
	Others	0.01	0.02	0.00	0.01	0.07	2.81
[Covariates] 5-year expected net return, $/acre planted	Corn	186.16	91.71	67.63	148.65	433.58	0.92
	Soybeans	133.51	117.59	0.00	126.43	380.37	0.58
	Wheat	101.49	51.26	28.22	86.36	217.49	0.54
	Other crops	158.19	90.80	65.41	131.95	471.10	2.24
	Pasture/Range	47.34	47.18	2.77	17.90	180.73	0.96
	Forest	118.28	150.35	0.00	65.02	613.40	1.93
5-year expected net return gap, $/acre planted	|Soybeans – Corn|	75.40	69.16	2.58	51.02	268.82	1.13
	|Wheat – Corn|	86.22	71.08	3.10	66.45	258.34	0.98
	|Other crops – Corn|	88.13	79.17	1.30	55.91	289.71	1.24
	|Pasture/Range – Corn|	140.52	90.26	0.98	119.69	344.24	0.65
	|Forest – Corn|	174.89	126.58	3.21	144.25	463.01	0.65
	|Wheat – Soybeans|	100.95	52.52	18.10	88.41	217.49	0.52
	|Other crops – Soybeans|	118.29	114.50	3.42	67.74	471.10	1.59
	|Pasture/Range – Soybeans|	90.83	85.40	2.77	70.23	280.22	0.94
	|Forest – Soybeans|	166.89	134.95	7.77	134.10	613.40	1.31
	|Other crops – Wheat|	62.25	60.98	1.87	44.03	290.26	2.26
	|Pasture/Range – Wheat|	59.20	48.79	2.98	48.10	202.55	1.19
	|Forest – Wheat|	114.99	109.74	1.29	80.48	475.11	1.98
	|Pasture/Range – Other crops|	111.07	103.69	3.95	85.70	452.52	2.03
	|Forest – Other crops|	136.56	105.12	16.66	97.26	403.73	1.42
	|Forest – Pasture/Range|	107.35	130.45	3.77	70.26	604.52	2.33

net return for forest activity. Timber production revenue uses the saw timber cut prices (U.S. Department of Agriculture, Forest Service (USDA-FS), 2020a). Unlike annual crop production, trees need multiyears for timber production. Therefore, the deterministic Faustmann formula (Buongiomo, 2001) is the approach approximating timber returns based on the 5% discounted present values over an infinite period. For the calculation, the tree yields and acres of forest are necessary per species and tree age (Smith et al., 2006; USDA-FS, 2020b).

Crop production and pasture/range activities use the revenue–cost ratio (FAPRI and AMAP, 2021) to complete the derivation of the net returns. Trees' planting and management costs

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subtracted from tree total revenues allow for optimizing discounted present values of the net return with respect to the age of trees (Dubois et al., 2001, 2003; Moulton and Richards, 1990; Smidt et al., 2005; Folegatti et al., 2007; Barlow et al., 2009; Barlow and Dubois, 2011; Dooley and Barlow, 2013; Maggard and Barlow, 2017). All state net returns are weighted by the ratio of acres planted or covered by each category so that quinquennial FPR net returns are finally calculated as the arithmetic average for every 5 years of the annual observations between 1992 and 2017. Table 1 also describes the positive skewness, large standard deviation, and difference between means and medians among the covariates. Therefore, observations are normalized before the estimation.

4. Empirical Model

The model assumes that the post-CRP land-use share follows the Dirichlet distribution to cope with the bias risks associated with aggregated data and transformation of proportional dependent variables. However, the data sample contains zeros for land-use alternatives, presumably because the land attributes and climate factors forced landowners to choose other options, as noted in Section 3. To avoid the out-of-boundary problem with zero in Dirichlet distribution, we follow the approach of Tsagris and Stewart (2018). Let $\mathbf{Y}$ denote the post-CRP land-use share vector of all alternatives subscripted by $j = 1, \ldots, M$, and $\mathbf{Y}$ splits into O groups corresponding to all possible subsets of non-zero components. Further, a vector G with 1s and 0s indexes non-zero components of $\mathbf{Y}$ for each group o where $o = \{1, \ldots, O\}$, and θ_o denotes the marginal probability that an observation falls into a group o. If $\mathbf{Y}$ takes specific nonzero components in a group $o^{\star}$, the density of $\mathbf{Y}$ is the conditional probability of $\mathbf{Y}$ given an indicator vector $g_{o^{\star}}$ multiplied by the corresponding $\theta_{g_{o^{\star}}}$ because the probability that Y is not in $o^{\star}$ should be zero. Then, the Dirichlet distribution of $\mathbf{Y}$ containing nonzero components in the subset $o^{\star}$ ($\mathbf{Y}_{o^{\star}} \sim \mathrm{Dir}(\alpha_{o^{\star}}, \phi_{o^{\star}})$) has a density with $\theta_{o^{\star}}$ as follows:

$$f(y) = \sum_{o=1}^{O} f(y, g_o) = f(y, g_{o^*}) = f(y|g_{o^*})\theta_{o^*} = f(y_{o^*})\theta_{o^*} \tag{2a}$$

where

$$f(y_{o^*}; \phi_{o^*}, \alpha_{o^*}) = \frac{\Gamma\left(\sum_{j=1}^{M_{o^*}} \phi_{o^*}\alpha_{o^*j}\right)}{\prod_{j=1}^{M_{o^*}} \Gamma\left(\phi_{o^*}\alpha_{o^*j}\right)} \prod_{j=1}^{M_{o^*}} y_{o^*j}^{\phi_{o^*}\alpha_{o^*j}-1}. \tag{2b}$$

A Function (2b) is the Dirichlet density of $\boldsymbol{y}_{o^{\star}}$ with a mean vector $\boldsymbol{\alpha}_{o^{\star}} = [\alpha_{o^{\star}j}]_{(M^{o^{\star}} \times 1)}$ and a precision parameter $\varphi_{o^{\star}}$. The mean parameter has the sum-to-one condition, $\sum_{j=1}^{M_{o^*}} \alpha_{o^*j} = 1$ while the precision parameter is the summation of concentration parameters, $\phi_{o^*} = \sum_{j=1}^{M_{o^*}} a_{o^*j}$. $a_{o^*j} > 0$ is a positive real number for all j, and it defines a shape or position where components concentrate with high probabilities in the standard $M_{o^{\star}} - 1$ simplex.

The Dirichlet regression defines that the mean and precision parameters are linked with strictly increasing and twice differentiable functions with explanatory variables and coefficient parameters (Cribari-Neto and Zeileis, 2010; Douma and Weedon, 2019). Although O different sets of coefficient parameters can exist due to mean and precision parameters for nonzero components subsets, statistical reliability and computational efficiency are hard to secure as the dimension of the $\mathbf{Y}$ becomes large because sample numbers of some groups are likely to be small. Therefore, the assumption of the same regression parameters across the groups (Bear and Billheimer, 2016; Tsagris and Stewart, 2018) is introduced by employing a selection matrix Q_o for each group o to deal with the empirical complication. The matrix identifies nonzero elements with 1, but all

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others are zero.[2] Therefore, the ZADR model for the post-CRP land transition is defined by the density (3a) and link functions of its mean and precision parameters as follows:

$$f(\mathbf{y}) = f(y_{o^*}; \Phi, \gamma, \theta_{o^*}) = \frac{\Gamma\left(\sum_{j=1}^{M_{o^*}} \phi \mathbf{Q}_{o^*} \alpha^*[j]\right)}{\prod_{j=1}^{M_{o^*}} \Gamma\left(\phi \mathbf{Q}_{o^*} \alpha_*[j]\right)} \prod_{j=1}^{M_{o^*}} y_{o^* j}^{\phi \mathbf{Q}_{o^*} \alpha^*[j]-1} \theta_{o^*} \tag{3a}$$

where

$$\mathrm{logit}(\mathbf{Q}_{o^*} \alpha^*[j]) = \mathbf{X}_j \beta_j + \mathbf{Z}\gamma \quad \forall \quad j = 1, \ldots, M_{o^*}, \tag{3b}$$

$$\ln \phi = d \tag{3c}$$

The link function for the mean parameter (3b) is modeled on the logit function of a covariate matrix $\mathbf{X}_j$ for each j with coefficient parameter $\boldsymbol{\beta}_j$ and a regional one-hot[3] encoding matrix $\mathbf{Z}$ if regional fixed factors $\boldsymbol{\gamma}$ are considered to include in the model for specifying the regional heterogeneities. A logarithmic function (3c) links the precision parameter with a constant term d for the estimating efficiency even if it is possible to connect with a linear combination between explanatory variables and coefficient parameters.

Although Tsagris and Stewart (2018) uses maximum likelihood estimation (MLE), the sample size of the present study is too small to secure statistical confidence based on the frequentist approach. Also, the computational burden could increase under the MLE by considering the regional fixed effects of the model as in the case of a beta regression (Liu and Kong, 2015). Therefore, we use the Bayesian approach. Bayes' rule derives posterior distributions of parameters $\boldsymbol{\Phi} = [\beta_1, \ldots, \beta_M, d, \boldsymbol{\Sigma}\ ]$ and $\boldsymbol{\gamma}$ from the likelihood and priors,

$$\begin{aligned} f(\Phi, \gamma, \theta; \mathbf{Y}, \mathbf{X}) \quad & \propto L(\mathbf{Y}, \mathbf{X}; \Phi, \gamma) \\ & \propto L(\mathbf{Y}, \mathbf{X}; \Phi, \gamma) f(\gamma; \Phi) f(\Phi) \\ & \propto L(\mathbf{Y}, \mathbf{X}; \Phi, \gamma) f(\gamma; \Phi) \prod_{j=1}^{M-1} \prod_{k=0}^{K} f(\beta_{jk}) f(d) f(\Sigma). \end{aligned} \tag{4}$$

where $\boldsymbol{\Sigma}$ is the covariance matrix with zero off-diagonal elements and $\boldsymbol{\theta}$ is a vector of marginal probabilities of $o = 1, \ldots, O$. K is a number of explanatory variables. The model assumes that θ_o is only relevant to the posterior distributions as a constant because a relative frequency of sample size N_o of a group o (or N_o/N) can be the maximum likelihood estimator of the parameter (Tsagris and Stewart, 2018). Also, all elements in $\boldsymbol{\Phi}$ are assumed to be independent of each other so that $f(\boldsymbol{\Phi}) = \prod_{j=1}^{M-1} \prod_{k=0}^{K} f(\beta_{jk}) f(d) \prod_{i=1}^{7} f(\sigma_{ii})$ where σ_{ii} is the diagonal elements in $\boldsymbol{\Sigma}$ for all $k = 1, \ldots, K$ explanatory variables. Therefore, $\boldsymbol{\beta}_j$, $\boldsymbol{\gamma}$, d, and $\boldsymbol{\Sigma}$ are parameters that have a prior distributions. The finally selected prior distributions are described in Figure 1. The parameter $\boldsymbol{\beta}_j$ follows the normal distribution $N(\mu_{\beta_{jk}}, \tau_{jk})$ where $\mu_{\beta_{jk}} \sim \mathrm{U}(0, 1)$ if $j = k$ but $\mu_{\beta_{jk}} \sim \mathrm{U}(-1, 1)$ otherwise, and $\tau_{jk} \sim 1/\mathrm{Exp}(10^{-1})$ for all j, k. However, the intercept β_{j0} is distributed normally with mean zero and precision followed by $U(0, 10^3)$. For the regional fixed parameter $\boldsymbol{\gamma}$, it follows multivariate normal distribution $N(\mu_\gamma, \boldsymbol{\Sigma}\ )$ where mean $\mu_{\gamma_i} \sim U(-1, 1)$ for all i but diagonals of covariance $\boldsymbol{\Sigma} \sim U(0, 10^{-3})$ but zeros otherwise. The constant term, d, for the precision

[2]For example, the first group $o = 1$ corresponding to the seven components of $\mathbf{Y}$ has a non-zero value at the second and fifth elements. Consequently, the matrix $\mathbf{Q}_1$ will be

$$\mathbf{Q}_1 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

[3]One-hot encoding is a binary variable corresponding to the number of categories. Since seven regions are defined, the matrix dimension should be $N \times 7$, where N denotes the number of samples. While the number of dummy variables is six, the zero vector represents the last category.

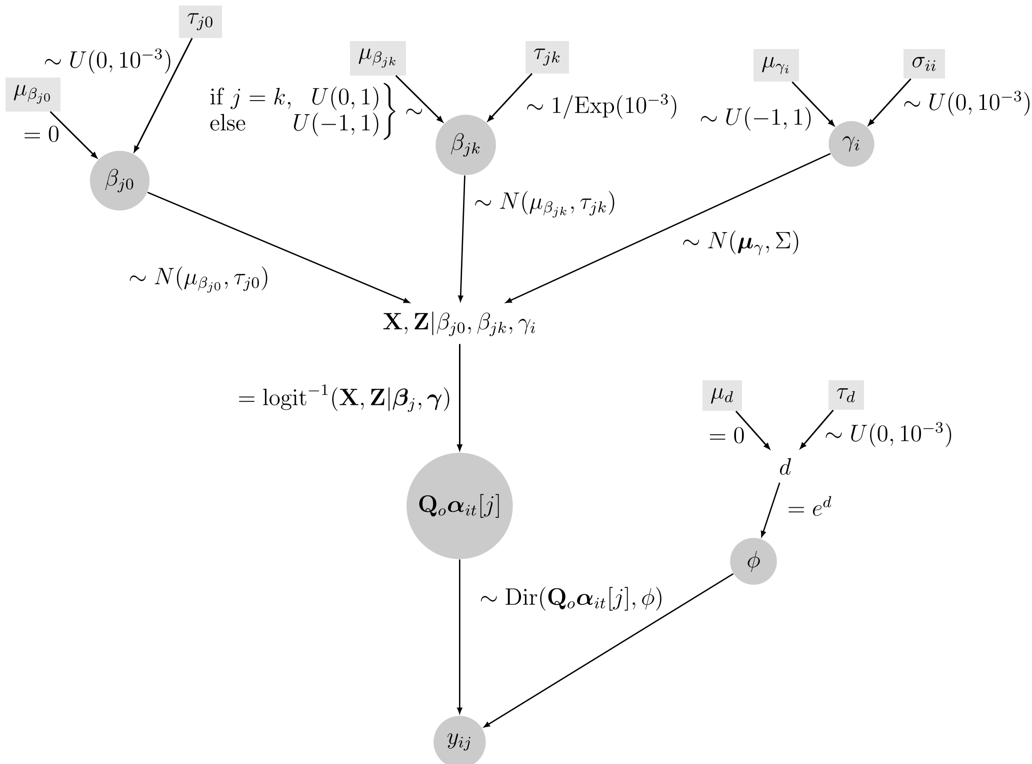

Figure 1. ZADR model diagram – the set of priors selected for the estimation. Light gray rectangular represents a parameter assuming a hyper prior, while the gray circle indicates a parameter following a prior distribution to estimate posterior distribution. All parameters follow the distributions selected or are determined as a constant value. The notations next to the arrows refer to the specific set of those. The direction of the arrow indicates the order of the coding algorithm.

parameter of the zero adjusted Dirichlet distribution also follows $N(0, \tau_d)$ where $\tau_d \sim U(0, 10^{-3})$. All details about the likelihood and prior settings are described in the Appendix A.1.

5. Trade dispute analysis

After estimation, the model is used for applied analysis. The scenarios consider how the US–China trade dispute, MFP payments, and Phase 1 deal between the two nations affected land use. The base scenario (Base) assumes that the bilateral trade dispute happened without the Phase 1 deal but with the MFP payments. The base scenario employs certain market projections (FAPRI AMAP, 2020) and the upper bound estimates of the MFP payments.[4] FAPRI model projects market production and producer prices for the next 10 years based on assumptions of market circumstances. The report (FAPRI AMAP, 2020) provides two projections depending on the different assumptions. One is that the bilateral trade dispute remains in place, and the other includes the possible outcome of Phase 1 implementation. The method of calculating the two MFP payments follows the program provisions (USDA-FSA, 2018, 2019a, 2019b), except it does not

[4]The payment is estimated by multiplying the total production or acre planted (USDA-NASS, 2020) by the MFP payment rates without considering the income eligibility and payment cap based on a method used by Congressional Research Service (Schnepf, 2019; Schnepf et al., 2019) and the Farm Bureau (2018b, 2019). The estimates, therefore, may be different from the actual payment and can be interpreted as the upper limit of the payment. The payment estimation is described in Table A2 of the supplementary materials.

consider payment limitations or the effect of prohibiting payments to producers with adjusted gross income above a cap. Based on the two annual projections and the MFP payments, crop production's 5-year average net returns are allowed to calculate in various situations. For comparison, there are two different alternative scenarios as follows:

- Scenario 1 (S1): The Phase 1 deal suspends the bilateral trade dispute between the two nations. MFP payments are made in 2018 and 2019 but not in subsequent years.
- Scenario 2 (S2): The bilateral trade dispute continues without the Phase 1 deal and MFP payments.

The base scenario represents the situation without the Phase 1 agreement. Scenario S1 implies the situation after the Phase 1 deal to see the trade agreement's impact. Scenario S2 indicates the what-if circumstances of no MFP payments to farmers without the Phase 1 deal for estimating the impact of MFP payments. Other situations could also be explored. To derive net returns for any scenario, it is necessary to make additional assumptions. For example, Scenario S2 assumes there are no MFP payments during the bilateral trade dispute, although this was not the case before the implementation of the Phase 1 agreement. However, the observations used in estimation preceded the first MFP payments so any impact of the payments on the land use decisions is an extrapolation. Therefore, the model performance is expected to be lower in Scenario S1, with these payments, than in the case of scenario S2 without MFP payments.

Scenario S1 raises the question of how the MFP affects land-use decisions. Land-use decisions might be based on expected future returns that exclude such temporary payments on the assumption that they will not be repeated. Alternatively, expected future returns might include MFP payments based on the belief that policy makers will choose to offset future losses with these payments. There is ex-post support for both points of view. An additional round of MFP payments, albeit with a different payment structure, was made for crops planted in 2019. However, no MFP program was put in place for 2020 or 2021, perhaps because policy makers decided the Phase 1 agreement obviated the need for a program to offset trade losses. Instead, producers received payments under a distinct round of ad hoc payments to compensate producers for the market impacts of the coronavirus crisis. In Scenario S1 and in the base case (Base) analysis here assumes land managers believe MFP payments indicate future returns.

Scenario S2 simulates the hypothetical case without expected future MFPs. There is a limitation to comparing the assumptions and results with the base scenario. The 2018 MFP has a commodity production-based payment rate, and eligible commodities were already planted or harvested before the announcement. The 2019 MFP payment, in contrast, was announced before farmers had completed planting the eligible commodities. In each county, the same per-acre payment was made on any land planted to an eligible crop, with payment rates determined by a weighted average of estimated trade damage to eligible nonspecialty crops produced in the county. While the first MFP may not have affected the production of eligible crops in 2018, the same appears less likely for the 2019 program. Farmers could consider the additional MFP payment to produce eligible crops when deciding the total number of acres to plant, although the payments were not tied to current yields or the specific eligible crops planted. The only way to receive the 2019 MFP payment was to plant one or more of the eligible crops, so the program may have resulted in more acres planted than would have occurred in the absence of the program.

Based on the three scenarios, projections, and MFP payment observations, Table 2 describes the net returns of four crop production categories for each scenario. In scenario S1, compared to the base scenario in Table 2, the sum of crop net returns and MFP payments increases by 0.9% to 10.5% for all of the FPRs. The net returns for corn and soybeans production experience higher increases than for wheat and other crops because the Phase 1 deal is estimated to have a larger impact on the prices of soybeans and corn than other commodities. In scenario S2, the sum of net returns and MFP payments in all regions are reduced by 1.8%–14.4%. For soybeans, for example,

Table 2. Net returns by crop production, region, and scenario

Scenario	Region	Net Returns ($/Acre Planted), 2017-2022					
		Corn	Soybeans	Wheat	Other Crops	Pasture/Range	Forest
Base	Corn belt & Lake States	271.4	289.6	122.8	146.3	129.1	14.2
	Mountain	165.2	0.0	70.3	164.1	4.8	11.3
	Northeast	175.0	231.2	92.6	151.1	180.8	99.2
	Northern Plains	200.5	190.2	84.5	129.7	23.2	0.0
	Pacific	101.3	0.0	90.4	326.8	18.6	123.3
	Southeast	196.1	232.0	85.1	135.8	113.5	43.0
	Southern Plains	164.3	203.8	58.8	85.6	11.5	28.0
S1	Corn belt & Lake States	279.3	297.6	124.6	147.7	129.1	14.2
	Mountain	170.7	0.0	71.5	166.2	4.8	11.3
	Northeast	180.6	238.0	94.2	152.5	180.8	99.2
	Northern Plains	207.5	210.3	86.0	135.8	23.2	0.0
	Pacific	104.2	0.0	91.8	330.5	18.6	123.3
	Southeast	202.1	238.7	86.5	137.1	113.5	43.0
	Southern Plains	169.2	210.1	59.9	87.8	11.5	28.0
S2	Corn belt & Lake States	260.7	264.2	112.0	140.6	129.1	14.2
	Mountain	162.2	0.0	66.6	160.4	4.8	11.3
	Northeast	168.6	211.4	87.5	147.0	180.8	99.2
	Northern Plains	192.3	170.5	76.7	120.2	23.2	0.0
	Pacific	97.1	0.0	84.7	320.4	18.6	123.3
	Southeast	184.6	207.1	76.6	122.2	113.5	43.0
	Southern Plains	155.3	190.8	50.4	74.7	11.5	28.0

Source: FAPRI AMAP (2020), USDA-FSA (2018, 2019a, 2019b).

the return decreases by more than 10% in Northern Plains and Southeast because of the loss of MFP payments in the scenario.

6. Results

6.1. Sensitivity of Predictions and Elasticity estimates

In Beta or Dirichlet regression models, the posterior distributions of coefficient βs do not indicate the marginal effect of expected land-use net returns to post-CRP land-use shares since the dependent variables are not linear relations with explanatory variables (Lee, 2020; Liu and Kong, 2015). Instead, we examine how posterior predictive samples change due to a shock to each net return variable at a time starting from the Base scenario. Expected net returns (Table 2) derive the posterior predictive samples from the model for the Base scenario in Table 3.

Results from the sensitivity simulation are described in Table 4 for the three crops. Net returns of certain activities are changed by 1% or 50%, positive or negative, one at a time to obtain posterior prediction changes for each activity and FPRs from the base level. The units are expressed in 1,000 acres by multiplying the samples by the maximum CRP acres that could leave the program

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Table 3. Summary of posterior predictive sample for the Base scenario

		Post-CRP Land-Use Transitions (1,000 Acres) to		
Region	Statistic	Corn	Soybeans	Wheat
Corn Belt & Lake States	Mean	540.57	710.27	183.76
	Median	483.60	639.75	111.39
	95% HDI	[0.11, 1, 195.57]	[0.00, 1, 593.78]	[0.00, 611.62]
	S.D.	343.62	468.98	208.98
Mountain	Mean	442.13	0.00	347.31
	Median	363.67	0.00	249.29
	95% HDI	[0.00, 1, 116.52]	[0.00, 0.00]	[0.00, 1, 013.73]
	S.D.	348.42	0.00	334.20
Northeast	Mean	24.69	20.44	73.39
	Median	18.94	11.81	72.90
	95% HDI	[0.00, 68.45]	[0.00, 69.61]	[9.95, 135.89]
	S.D.	21.91	23.79	34.19
Northern Plains	Mean	366.97	420.03	327.66
	Median	305.28	357.27	268.60
	95% HDI	[0.03, 918.44]	[0.01, 1, 012.39]	[0.12, 828.91]
	S.D.	279.99	303.67	256.76
Pacific	Mean	0.00	0.00	145.20
	Median	0.00	0.00	107.96
	95% HDI	[0.00, 0.00]	[0.00, 0.00]	[0.00, 423.33]
	S.D.	0.00	0.00	134.92
Southeast	Mean	183.26	217.16	166.70
	Median	156.69	171.04	134.49
	95% HDI	[0.00, 443.76]	[0.00, 587.40]	[0.00, 434.31]
	S.D.	133.44	183.08	136.55
Southern Plains	Mean	194.14	0.00	340.92
	Median	142.60	0.00	277.72
	95% HDI	[0.00, 562.02]	[0.00, 0.00]	[0.00, 886.78]
	S.D.	179.94	0.00	273.25

over the next 5 years from 2017 (USDA-FSA, 2020).[5] Those estimates provide insights into the average marginal effects of the net returns. Section A3 in the supplemental materials reports the rest of the national and regional results for other agricultural activities.

Each row indicates the area response to a net return shock. A column represents the average changes in acres transitioning to three crops after exiting the CRP due to the net return shocks. For

[5]Although the acres that already left the CRP are the source for more accurate estimates because of the definition for the dependent variable in Equation (1), the full data for 2020 were not available to the public. Table A11 in the supplementary document describes the simulation with CRP acres exiting the program in 2020.

Table 4. Sensitivity of posterior predictive sample means to net returns variables

		Post-CRP Land-Use Transitions (1,000 Acres) to		
		Corn	Soybeans	Wheat
Base scenario		1, 751.76	1, 367.89	1, 584.93
Shock, %	Net return shocked	Change (1,000 acres) from the Base		
+ 01	Corn	22.64(1.29)	9.68(0.71)	− 13.45(−0.85)
	Soybeans	− 3.59(−0.21)	19.75(1.44)	2.67(0.17)
	Wheat	20.16(1.15)	− 8.88(−0.65)	3.84(0.24)
+ 50	Corn	99.34(0.11)	− 870.72(−1.27)	− 504.28(−0.64)
	Soybeans	− 784.06(−0.90)	90.86(0.13)	576.91(0.73)
	Wheat	− 35.25(−0.04)	− 146.83(−0.21)	677.95(0.86)
−01	Corn	− 6.15(0.35)	− 9.89(0.72)	22.27(−1.41)
	Soybeans	22.54(−1.29)	− 11.61(0.85)	− 11.50(0.73)
	Wheat	9.76(−0.56)	4.84(−0.35)	− 0.33(0.02)
−50	Corn	− 825.17(0.94)	− 848.80(1.24)	1, 144.18(−1.44)
	Soybeans	− 349.53(0.40)	− 1, 142.33(1.67)	− 12.75(0.02)
	Wheat	− 120.29(0.14)	353.04(−0.52)	− 18.42(0.02)

Values in parentheses are arc elasticities of post-CRP land-use transitions with respect to net return changes between two posterior sample mean points.

example, a 1% increase in corn net returns increases the post-CRP area shifting to corn production by 22,640 acres from the Base scenario (top left entry of the table), as compared to 1.75 million acres total that transitioned to corn (top of Table 4). Estimates in parentheses indicated the (arc) elasticities for return changes between two posterior sample mean points.

The posterior predictive averages of post-CRP acres positively respond to their own net returns. Furthermore, sensitivities returning to corn and soybean production decrease as the size of the shock to net returns increases. Conversely, acres going to wheat cropping become more sensitive when the net return for wheat rises from 1 to 50%.

Average own return elasticities for the 50% increase in returns range from 0.11 to 0.86 a broader range than Roberts and Lubowski (2007). Similar to their results, the impact of negative change is more responsive than positive change for all crops except for wheat production. For example, we estimate a 0.13 elasticity of post-CRP land use to soybeans for a 50% expected return increase and a 1.67 for a decrease of the same magnitude, while Roberts and Lubowski estimate a 0.26 of post-CRP land use to crop for a 50% increase and a 0.33 for a decrease of the same magnitude.

Cross net return effects in the model are sensitive to the magnitude of shocks. For a 1% change in returns, several cross effects indicate an unexpected complementary relationship among crops. However, for a 50% increase in returns, all cross-effects are negative, other than a positive impact of soybean returns on wheat area, which could be plausible in cases where wheat and soybeans are double-cropped on the same acreage. When returns are reduced by 50%, more unexpected complementary relationships are found.

6.2. Trade dispute impacts on land use

The scenario analysis now uses the posterior parameter distributions of the model to simulate each scenario's post-CRP land-use acre distributions. The difference in distributions between

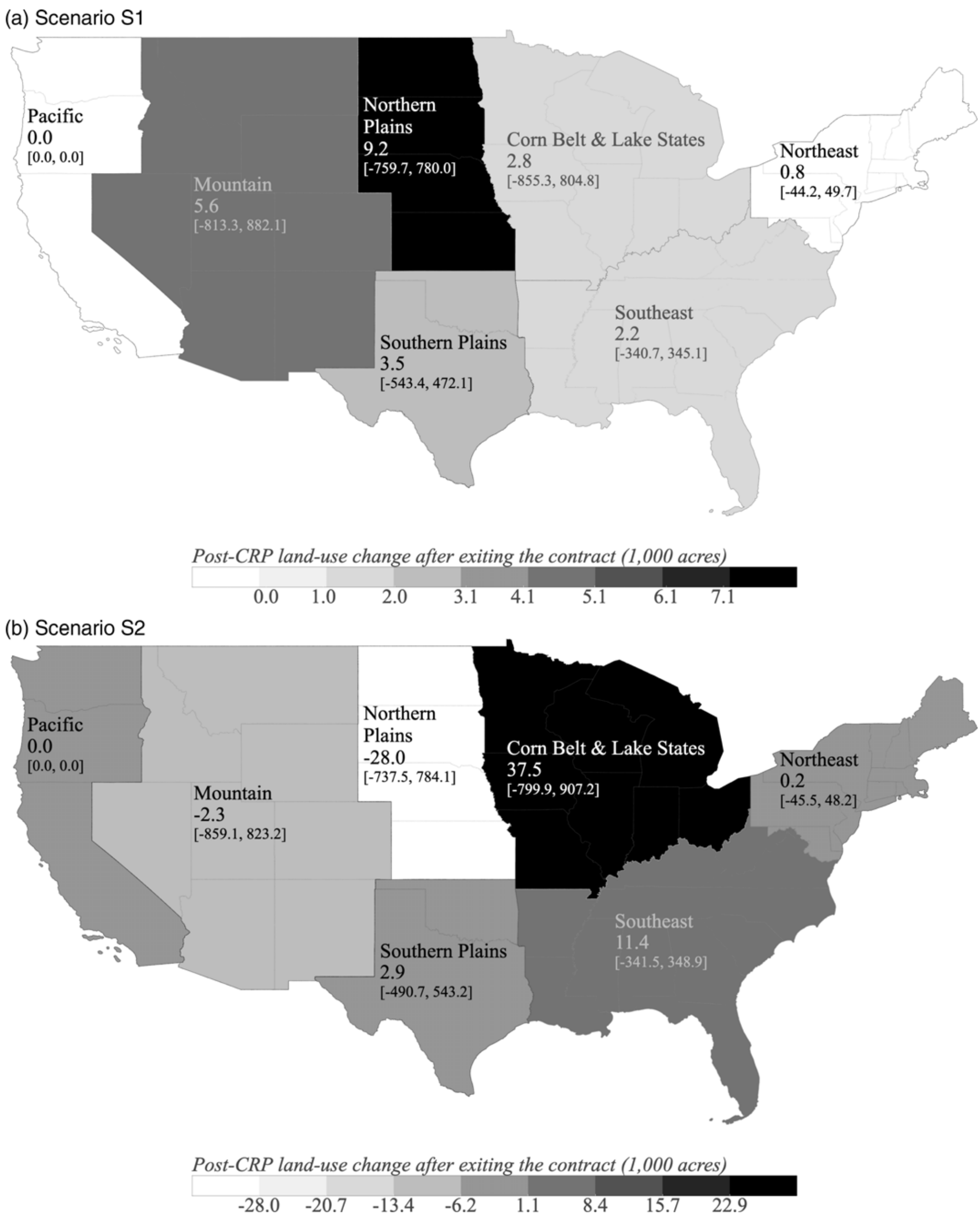

Figure 2. Posterior predictive sample difference in acres returning to corn production. (a) Scenario S1. (b) Scenario S2. Values below the FP regions are means of differences in post-CRP acres between the S1/S2 and Base. Values in square bracket are the 2.5 and 97.5% highest density interval boundary values.

alternative scenarios (S1 and S2) and Base (Table 3) can identify the bilateral trade war and MFP impacts on post-CRP land allocation to alternative agricultural activities. Figures 2–4 summarize these different distributions using mean values and the 95% highest posterior density intervals (HDIs) for the CRP acres going to corn, soybean, and wheat production after exiting program

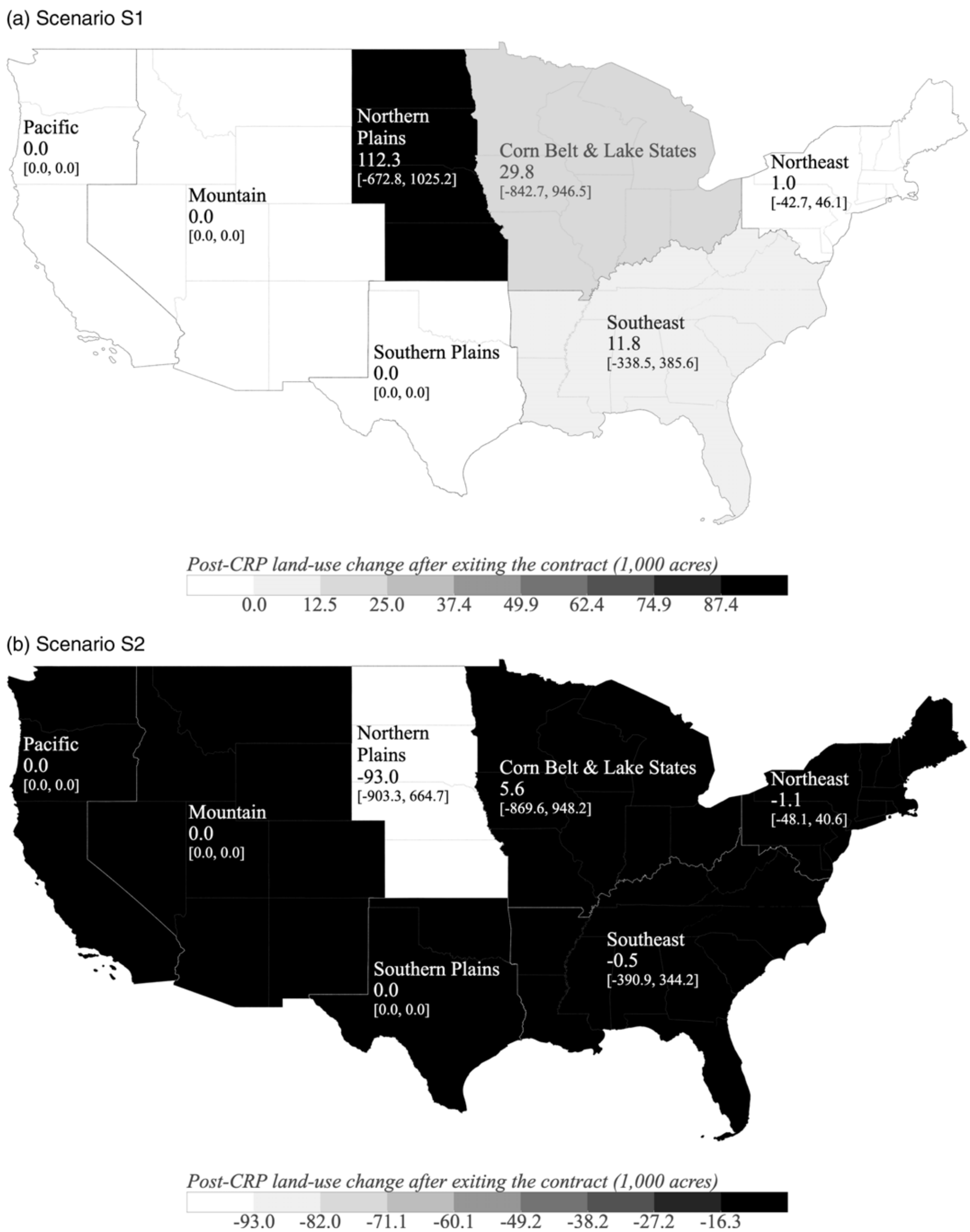

Figure 3. Posterior predictive sample difference in acres returning to soybean production. (a) Scenario S1. (b) Scenario S2. Values below the FP regions are means of differences in post-CRP acres between the S1/S2 and Base. Values in square bracket are the 2.5 and 97.5% highest density interval boundary values.

contracts. The post-CRP land-use changes for other agricultural activities can be found in Section A4 of the supplementary materials.

While the Phase 1 deal pushes all 5-year averages of crop net returns up in scenario S1, the increase in corn return is smaller than the increase in soybeans returns, except for regions with no

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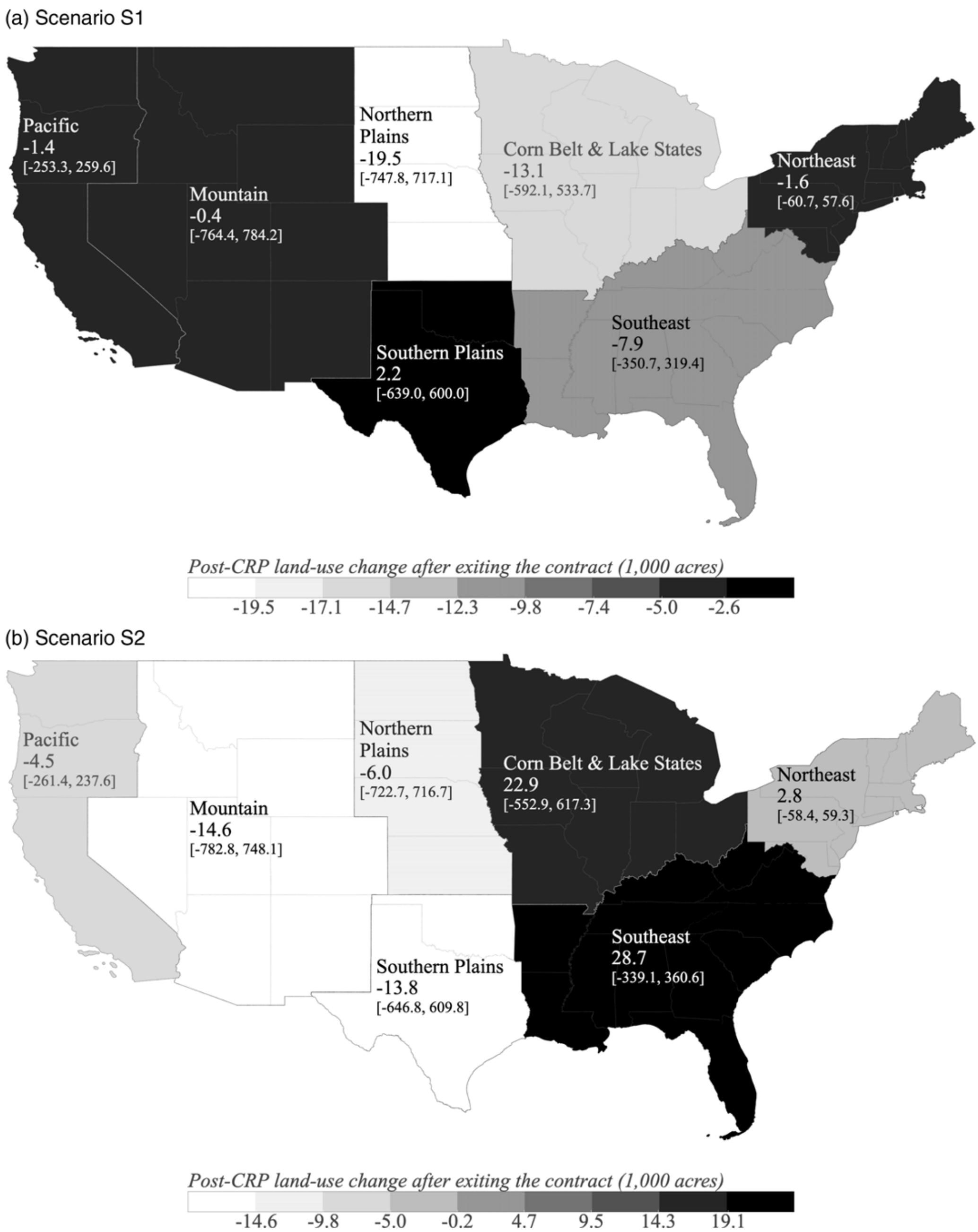

Figure 4. Posterior predictive sample difference in acres returning to wheat production. (a) Scenario S1. (b) Scenario S2. Values below the FP regions are means of differences in post-CRP acres between the S1/S2 and Base. Values in square bracket are the 2.5 and 97.5% highest density interval boundary values.

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record of soybean production (the Mountain and the Pacific). Therefore, land transitioning to corn increases less than soybeans in the Corn Belt and Lake States, the Northern Plains, and the Southeast, where corn and soybeans are notably produced.[6] With no land devoted to soybean production, the increase in corn net return results in a 6,000-acre increase in land transitioning to corn production in the Mountain region (Figure 2a). In the Northeast, CRP acres return to corn and soybeans in Scenario S1 than in the Base, although only 0.8–1.0 acre increase on average.

As soybean returns increase more than corn returns in the three notable corn and soybean producing regions, more acres return to soybean production in Scenario S1 relative to the baseline: an average of 30,000 more acres in the Corn Belt and Lake States, 112,000 more acres in the Northern Plains, and 12,000 more acres in the Southeast (Figure 3a). This result is consistent with larger increases in soybean net returns than in returns for other activities. Different response patterns across regions mostly reflect a difference in the importance of the various crops in overall land use in each region, reflecting differences in soil types and other agronomic factors.

The assumed change in net returns due to the US–China trade agreement is greater for soybeans and corn than for other activities. Therefore, acres going to other crops other than corn and soybeans are reduced in regions with corn and soybean production. For example, post-CRP acres transitioning to wheat decreased by 13,000 (Corn Belt and Lake States), 20,000 (Northern Plains), and 8,000 (Southeast) acres compared to the Base (Figure 4a).

All expected net returns for land-use activities are reduced from the base scenario if there are no MFP payments and no trade deal (Scenario S2 compared to the Base). All else equal, reductions in each net return would reduce the number of acres transitioning to each crop, but the impacts on returns to competing crops must also be considered. For instance, average post-CRP land-use transitions to corn, soybean, and wheat production in the Northern Plains region decrease by 28,000, 93,000, and 6,000 acres (Figures 2b–4b), but in the Corn Belt and Lake States, Northeast, and Southeast regions, transitions to corn and wheat production increase because of cross effects. The relative reductions in net returns to different activities affect the results, as does the mix of crops grown in a particular region. Scenario S2 lessens the gap in net returns between corn and soybeans and between wheat and soybeans by \$13 and \$16 per acre, which is greater than the own net return reductions (\$5–\$12/ per acre). Hence, three regions see an increase in corn and wheat production after exiting the CRP as the positive impact of reducing the return gap surpasses the negative impact of the decrease in their own net returns. These cross effects are sufficiently strong in the model that Corn Belt and Lake State area transitioning to soybeans actually increases slightly in scenario S2, contrary to expectations.

7. Conclusion

This paper estimates elasticities governing the land transition from CRP to crop and other uses. It also applies these findings to the US–China trade dispute to demonstrate their value to applied land-use economics. Those estimated transitions were generally consistent with expectations about land-use optimization given region-specific characteristics, expected net returns of possible alternatives, and costs to convert from the conservation practices during the enrollment in the program.

Own-net returns elasticities are positive and inelastic, and elasticities are sensitive to the magnitude and direction of changes in returns. The range of estimated elasticities is broader than the estimates from previous studies.

The Phase 1 deal raises expected net returns for all the crops analyzed by alleviating the impacts of the US–China trade dispute. The agreement causes more CRP land returning to crop

[6]For example, corn and soybeans account 42.0% of agricultural acres in the Corn Belt and Lake States, 25.4% in the Northern Plains, and 15.7% in the Southeast as measured by the Olympic average over the previous 5-marketing years from 2012 (USDA-NASS, 2020; USDA-NRCS, 2020).

production, with soybean acreage increasing more than area planted to other crops. This result is consistent with a larger increase in net returns for soybeans relative to other crops, and it may also be less costly to convert land exiting CRP to soybean production rather than for other uses.

Without MFP payments, a continued US–China trade dispute would decrease expected net returns and payments for crop production. Model results confirm that the likely consequence is a reduction in transitions of CRP acreage to crop production. Impacts on particular crops are sensitive to both own- and cross-net return effects.

The estimation presented in this paper is a novel assessment of post-CRP land transition to the four crops production and other land uses on a regional basis. In addition to an application to the bilateral trade dispute, the Bayesian approach with the ZADR model is introduced to the land-use analysis.

The previous approaches for the count-based proportions can analyze an individual discrete decision, so land parcel level data are required. However, protecting landowners' privacy restricts individual land use data access. While the previous methods can use the proportions derived from total land acres, aggregates by region broader than the county have the their own issues. ZADR model, however, has a chance of allowing total land use data broader than county level to estimate parameters without transformation of dependent variables by linking the exploratory variables into mean parameters of Dirichlet distribution that the land-use share assumed to be followed.

Although frequentist methods can estimate the ZADR model with maximum likelihood estimation, there is a risk regarding the statistical confidence in case of a small sample size in addition to the computational burden. Instead, the Bayesian approach has the benefit of estimating posterior distributions of parameters with small observations to understand the impact of the trade dispute and corresponding interventions. Even though the 95% HDIs of the posterior predictive samples are broad due to the small sample size, estimation informs policy makers that it confirms that the change in post-CRP land use returning to four specific crop categories is similar to the corresponding previous estimates.

This innovative method can and should be improved as scientists apply them to other critically important questions relating to CRP land use, including contract renewal decisions or how post-CRP land use choices relate to greenhouse gas emissions and climate change policies.

Supplementary material. To view supplementary material for this article, please visit https://doi.org/10.1017/aae.2023.3

Data availability statement. The data that support the findings will be available in the corresponding author's GitHub repository: https://github.com/muwizayeon/PyZADR/tree/dataset

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Conflict of interest. None.

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A. Appendix

A.1. Likelihood and the Bayesian priors

For the posterior density, the likelihood $L(\mathbf{Y}, \mathbf{X}; \mathbf{\Phi}, \gamma)$ in equation (4) can be defined by using the density (3a). Suppose that there are O groups (or population) for the land-use shares $\mathbf{Y}$ so that the sample observation S are also partitioned by O different groups such as S_o where $S \equiv \cup_{o=1}^{O} S_o$. Then the log likelihood $\ell = \ln L(\mathbf{Y}, \mathbf{X}; \mathbf{\Phi}, \gamma)$ becomes

$$\begin{aligned} \ell &= \ln\left[\prod_{o=1}^{O}\prod_{\{i|S_{oi}\in S_o\}}\prod_{\{t|\mathbf{y}_{oit}\in S_{oi}\}}\left(\frac{\Gamma\left(\sum_{j=1}^{M_o}\phi\mathbf{Q}_o\alpha_{it}[j]\right)}{\prod_{j=1}^{M_o}\Gamma(\phi\alpha_{it}[j])}\prod_{j=1}^{M_o}y_{oijt}^{\phi\mathbf{Q}_o\alpha_{it}[j]-1}\right)\theta_o\right] \\ &= n\ln\Gamma(\phi) - \sum_{o=1}^{O}\sum_{\{i|S_{oi}\in S_o\}}\sum_{\{t|\mathbf{y}_{oit}\in S_{oi}\}}\sum_{j=1}^{M_o}\ln\Gamma(\phi\mathbf{Q}_o\alpha_{it}[j]) \\ &\quad + \sum_{o=1}^{O}\sum_{\{i|S_{oi}\in S_o\}}\sum_{\{t|\mathbf{y}_{oit}\in S_{oi}\}}\sum_{j=1}^{M_o}(\phi\mathbf{Q}_o\alpha_{it}[j]-1)\ln y_{oijt} + \sum_{o=1}^{O}n_o\ln\theta_o \end{aligned} \tag{5a}$$

where

$$\mathbf{Q}_o\alpha_{it}[j] = \begin{cases} \frac{\exp(\mathbf{x}'_{ijt}\beta_j + \mathbf{z}'_i\gamma)}{1+\sum_{j'=1}^{M_O-1}\exp(\mathbf{x}'_{ijt}\beta_j + \mathbf{z}'_i\gamma)} & \text{if } j \neq M_O, \\ \frac{1}{1+\sum_{j'=1}^{M_O-1}\exp(\mathbf{x}'_{ijt}\beta_j + \mathbf{z}'_i\gamma)} & \text{else if } j = M_O, \end{cases} \tag{5b}$$

and

$$\phi = \exp(d) \tag{5c}$$

S_{oi} is the sample observation subset for a region i in S_o. n_o is a number of observations corresponding to a group o and $\sum_{o=1}^{O} n_o = n$, where n denotes the total number of observations. $\mathbf{Q}_o\alpha_{it}[j]$ is the jth nonzero element in a mean parameter vector $\boldsymbol{\alpha}$ corresponding to the group o in a region i at a period t. $\mathbf{x}_{ijt} = [x_{it,j}]_{(K \times 1)}$ is the covariate vector for the jth land-use share in a region i at a period t and $\boldsymbol{\beta}_j$ is the coefficient vector for the jth land-use share. When the model specifies the regional heterogeneities, there is a regional dummy vector $\mathbf{z}_i = [z_i]_{(N \times 7)}$ to estimate the regional fixed factor $\boldsymbol{\gamma}$.

Prior distributions on the intercepts, β_{j0}, assume the normal distribution $N(0, \tau_{j0})$ for all j. The precision parameters, τ_{j0}, follow the uniform distribution with intervals between 0 and 10^{-3}, denoted by $U(0, 10^{-3})$. The intercepts, therefore, are assumed to follow diffuse priors because their precision parameters are noninformative (or flat) to affect the posterior distributions minimally. Other parameters, β_{jk} where $k = 1, \ldots, K$, also follow the normal distribution $N(\mu_{\beta_{jk}}, \tau_{jk})$ while there are three hyper prior options for precision parameters, τ_{jk}, namely the uniform distribution $U(0, 10^{-3})$, the gamma distribution $\Gamma(0.1, 0.01)$, and the exponential distribution $1/\text{Exp}(10^{-3})$. We denote the priors of β_{jk} as L1 priors when the variance for j in i $(1/\tau_{jk})$ follows the exponential distribution and L2 priors if the precision parameters follow the gamma distributions. The uniform distribution on τ_{jk} priors implies a diffuse prior on β_{jk} as similar to the intercepts β_{j0}. L1 priors ignore the extreme outliers and shrink the parameters as in a LASSO regression, so the robustness of posterior parameter distributions will be improved. L2 priors can handle the collinearity of covariates since it regularizes parameters as in ridge regression. Therefore, L2 priors will improve the stability of coefficient parameters. The prior distribution of the constant d is also assumed to follow a normal distribution with mean zero and a precision parameter τ_d which can follow diffuse, L1, or L2 priors.

The hyper prior options for the mean parameter, $\mu_{\beta_{jk}}$, are zeros (diffuse) or assumed to follow the uniform distribution with specific intervals (weakly informative). Such a model could relate to net return elasticities of land-use change or price elasticities of acreage response to determine the upper and lower bounds of the uniform distributions' intervals. Estimated values commonly indicate that own net return or price elasticities are positive but inelastic (Barr et al., 2011; Kim and Moschini, 2018; Roberts and Lubowski, 2007; Sullivan et al., 2004). Cross net return elasticities are both negative and positive, but the absolute estimated values are smaller (more inelastic) than their own net return elasticities. Cross-price elasticities in the literature are also negative and more inelastic than own price elasticities (Kim and Moschini, 2018). However, previous studies did not estimate the net return elasticities of land use for the production of specific crops. Instead of using the previously observed values, we employ their theoretical properties, such as inelastic and positive own net return effect, and negative cross net return effect. The mean parameters, $\mu_{\beta_{jk}}$, therefore, have a uniform distribution $U(0, 1)$ for own-net returns but $U(-1, 1)$ for the absolute difference between own and cross net returns. The fixed regional factor parameter $\boldsymbol{\gamma}$ follows the multivariate normal distribution with mean $\boldsymbol{\mu}_{\gamma_i}$ and covariance $\boldsymbol{\Sigma}$. For the efficient calculation, the hyper prior of each μ_{γ_i} supposes to follow $U(-1, 1)$ for all i. The hyper prior assumption for $\boldsymbol{\Sigma}$ also has three options; diffuse, L1, and L2 priors are relevant because the covariances or off-diagonal elements are all zero.

The method used in this study chooses the model with the best fit among combinations of hyper priors, priors, and fixed factors. It is also necessary to compare posterior distributions from two different sample size groups. As the model only employ 35 observations, the five observations over time for each of the seven FPRs, model consistency over the sample size is crucial to show the robustness of scenario analysis. If the posterior predictive distributions are not likely to change as the sample size group adds one more observation to each FPR, the experiment provides evidence that the model is consistent and robust. Therefore, we also estimate results from subsamples. S9212 contains four quinquennial observations for each FPR from 1992 to 2012, while S9217 has five observations for each FPR by using the latest data. The model selection is described in detail in the supplementary material.

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