Effectiveness of Alternative Strategies for Nutrient Loss Reduction under Uncertainty

in the Racoon River Basin

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Abstract

Nitrogen (N) loss due to fertilizer intensive crops such as corn pose a threat to human and environmental health and is creating an imperative for strategies to reduce nutrient loss from agricultural fields. Cover crop adoption with annual row crops and diversification of crops to include perennial energy crops have been shown to be promising approaches to lower N leaching. These approaches differ in farmers costs, the trade-offs they offer in terms of short-term costs, long-term benefits, and the impact on food crop production. In the absence of policy incentives and markets for bioenergy, the adoption of these strategies is low. The design of policy incentives is complicated due to spatially varying nature of nutrient loss and uncertainties due to weather conditions. We apply a stochastic model with fine-scale data to examine the cost-effective mix of cover crop and perennial crop adoption to achieve N loss reduction targets for the Raccoon River Basin, Iowa, its implications for land use, food crop production, and farm profitability given varying bioenergy prices. We also examine the unintended effects of a biomass market for harvesting corn residues for bioenergy and its implications for N loss reduction. We find that a high biomass price can increase stover production from corn land which offsets the benefit of increased miscanthus production on N leaching reduction. In scenarios where policymakers prioritize reducing uncertainty in N loss, a decrease in corn production is expected to occur, inducing diminished N leaching but greater losses in farm profitability.

JEL Codes: Q18, Q24, Q25, Q56

Keywords: Cover crop, Nitrogen leaching, Perennial crop, Raccoon River Basin, Uncertainty

1. Introduction

Nitrogen (N) loss from excessive application of N fertilizer in the U.S. Corn Belt is one of the primary causes of water quality degradation within the Mississippi River Basin and the Gulf of Mexico (David et al., 2010; Jones, Nielsen, et al., 2018; Soriano et al., 2021) and presents a threat to public health and local economies due to contaminated drinking water sources and its impacts on fisheries, recreation, and tourism (EPA, 2016). In particular, nonpoint sources from agriculture play a substantial role in nutrient pollution in many watersheds. In 2015, U.S. congress amended the Safe Drinking Water Act and directed EPA to develop a strategic plan and implement watershed-based projects to reduce impacts to public health from nitrates in sources of drinking water.

Various strategies have been proposed to mitigate N leaching. One potential approach is adopting cover crops on the existing continuous corn or corn-soybean rotation lands, which does not conflict with food crop production and in the long run may improve crop productivity by improving soil health (Vendig et al., 2023). Studies have found that cover crop adoption can provide benefits for erosion, soil carbon, and greenhouse gas emissions (Deines et al., 2023; Ye et al., 2023) and help reduce N leaching (Kladivko et al., 2014; Waring et al., 2020). Specifically, the rye winter cover crop has been found to be able to significantly reduce drainage water nitrate concentrations by 42.5% to 61% over the first four years of the adoption (Kaspar et al., 2007, 2012; Malone et al., 2014). However, there are upfront cover crop adoption costs and short-term yield penalties from adopting cover crop practices, so the private cost of the cover crop adoption outweighs the short-term private benefit, leading to a low cover crop adoption rate. Therefore, although the cover crop adoption has several benefits (i.e., nutrient sequestering, soil health improvements, carbon dioxide removal, and biodiversity increases) (Schnitkey et al., 2023), there is no adequate incentives for farmers to adopt the cover crop practice, especially when they don't have prior experience with planting cover crops (Schnitkey et al., 2023). Thus, it is crucial to design policy incentives to enhance the cover crop adoption rate.

Another possible strategy to reduce N leaching is changing land use by replacing fertilizer-intensive row crops with perennial crops. Studies have shown that adopting perennial crops not only can reduce N leaching but also provide key ecosystem service while meeting the growing biomass demand due to the bioenergy mandate (Housh, Khanna, et al., 2015; Housh, Yaeger, et al., 2015; VanLoocke et al., 2017). Nevertheless, planting perennial crops on croplands can potentially conflict with food production (e.g., corn, soybeans). To minimize this conflict, perennial crops can be planted on idle (marginal) land if available, which are less suitable for food crop production. However, arable marginal land is limited, and planting perennial crops on marginal land may not necessarily be the most socially efficient approach to resolve the water quality issue because it does not displace continuous corn or corn-soybean production, which is the primary N source (Valcu-Lisman et al., 2016). Moreover, planting perennial crops involves high upfront costs, long time commitments, and reliance on demand for biomass and a high biomass price in order to be profitable. However, a high biomass price could incentivize more corn stover production and increase corn land, which can offset N loss benefit from perennial crops. Hence, the choice of appropriate crop mix to curtail N leaching given different biomass prices is a complex decision.

Due to several relative costs and benefits of cover crop and perennial crop adoption along with different implications to land use, N leaching, and farm profitability, it is crucial to investigate which crop mix is chosen on which landscape and what underlying mechanism is driving changes in land profitability and, in turn, land use. Since every policy and production practice has pros and cons, it is important to explore the effect of various strategies on N loss, land use, and farm profitability. Several factors can affect the profitability of land and land use decisions, such as slope gradient, erosion class, land capability, soil tolerance, climate, and hydrology (Valcu-Lisman et al., 2016), suggesting, instead of using coarse-resolution data (e.g., state, county, etc.), it is necessary to use fine-resolution data to consider land heterogeneity and identify the most optimal land allocation and crop selection (Brandes et al., 2016; Zhong et al., 2018).

The effectiveness of adopting cover crop and perennial crops on N loss reduction can be uncertain and depends on several factors, such as internal nutrient recycling rate (Amougou et al., 2012; Smith et al., 2013), hydrological processes (Castellano et al., 2010), residue decomposition (Palmer et al., 2014), and climate (Cowan et al., 2015; Kelliher et al., 2017). Moreover, the choice of crops and the type of land converted for bioenergy production can also have complex and uncertain effects on N losses (Whitaker et al., 2018). Therefore, considering the impact of N leaching and its uncertainties is crucial while designing cost-effective and sustainable strategies to reduce adverse consequences for the environment.

The Raccoon River Basin (RRB)[1] in west-central Iowa is a major contributor to high N loads in the primary drinking water source for Des Moines and hypoxia in the Gulf of Mexico (Goolsby et al., 2000; Hatfield et al., 2009a; Jones et al., 2016; Schilling & Zhang, 2004). The RRB watershed, dominated by corn-belt agriculture (Jha et al., 2010), has experienced increasing N leaching since 1970 (Hatfield et al., 2009b; Jones et al., 2018). With over 75% of the total land (934,400 ha) in the RRB used for row crop planting, corn alone accounts for more than 20% of the total land in the RRB (USDA-NASS, 2021). Thus, this study uses the RRB watershed (Figure 1)

[1] Due to the high levels of nitrates in the drinking water supply, the City of Des Moines invested $4 million in installing a water treatment plant in 1993, with a recent plan for building a new multi-million water treatment plant (EPA, 2016). Iowa Nutrient Reduction Strategy (2017) also aims to implement a nutrient removal process at the estimated annual cost of $114 million and sets 41% of the statewide total nitrogen reductions as the target load for nonpoint sources.

as a case study to investigate the effect of cover crop/perennial crop adoption and N reduction target policy on improving nitrate impairment while considering the uncertainty of N leaching.

Previous studies related to the impacts of corn production on water quality have often used deterministic approaches at the county (Housh, Khanna, et al., 2015; Housh, Yaeger, et al., 2015), sub-basin (Valcu-Lisman et al., 2016), or CRD levels (Chen et al., 2021; Chen, Debnath, et al., 2021; Ferin et al., 2021). To account for the uncertainty in N loss, this study applies a stochastic method to specify the probability of attaining the desired N leaching target load and investigate changes in the expected N leaching amount, land use, and agricultural profitability under different policy and biomass price scenarios. Due to land use changes affected by profitability and N leaching rate, which are often spatially heterogenous, this study also uses crop yield and N leaching data at a 10 km scale to capture the spatial heterogeneity in order to get more precise insight about distribution of land use, N loss management, and farm profitability.

The objective of this study is to employ a stochastic modeling approach with fine-scale data to investigate the effects of adopting a cover crop and perennial crops on land use, N leaching, and farm profits in the RRB, Iowa and to identify the associated cost of reducing N leaching and socially desirable land allocation while considering uncertainty in N reduction. Specifically, this study aims to explore the following research questions: first, this study investigates how adopting a cover crop and perennial crops improves N leaching while considering uncertainty in N reduction given different biomass prices. Second, the integrated assessment approach is applied to analyze to what extent perennial crops adoption, cover crop practice, and N regulation can reduce N leaching and what the corresponding costs and resulting land use implications are. Third, both grid- and county-scale data are used to examine differences in the estimated effects of N leaching reduction policies on land use changes and N leaching between using fine-scale and coarse-scale data.

This study contributes to the literature by exploring potential cost-effective policies to reduce N leaching in an agriculture-dominant watershed, applying a probabilistic approach to assess the policy effect on N leaching while accounting for N leaching uncertainties, and using different scales of data to derive modeling results and to identify potential benefits/drawbacks of adopting fine-scale data.

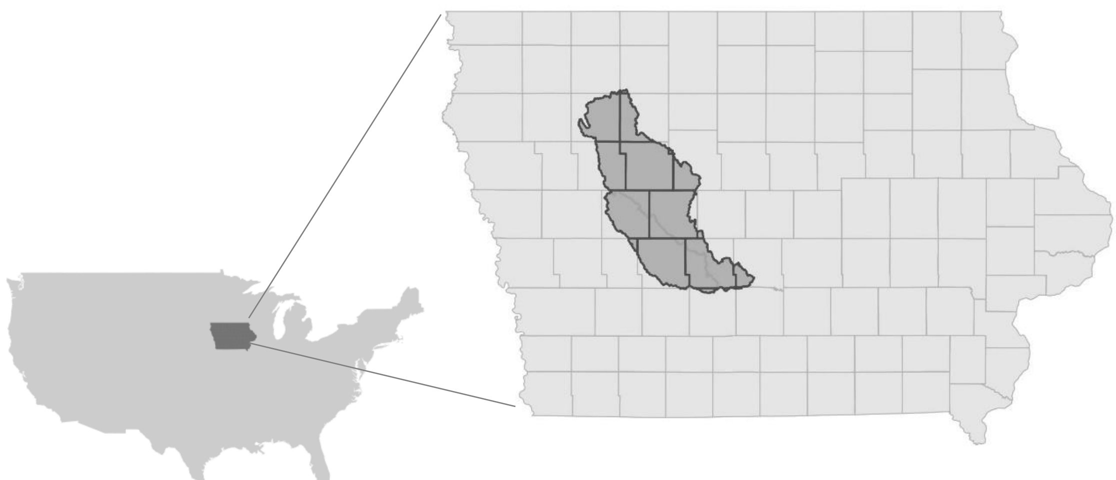


Figure 1. Study area: Raccoon River Basin Watershed, Iowa

2. Methods and Materials

2.1 Integrated modeling approach framework

The conceptual framework of this study is based on investigating the effect of adopting a cover crop and perennial crops along with an N reduction policy on land use change, N leaching, and farm profitability. The choice of crops depends on the profitability of each crop and the N leaching rate if an N regulation takes place. Adopting perennial crops relies on high biomass prices and usually takes years to get returns. Nevertheless, high biomass prices can also incentivize corn stover production and increase corn land demand, so finding a temporal land use and spatial crop mix decision to reduce N leaching while maximizing farms' profitability is a complicated decision-making problem. Furthermore, since N leaching, crop yield, and profitability are spatially varying, capturing the spatial heterogeneity in crop yield and N leaching data at a finer scale is important. Then, the decision-making problem expands to consider which crop mix to choose and where to plant the chosen crop mix to optimize N leaching and farm profitability. Moreover, due to the uncertainty in N loss, the effect of the chosen crop mixes on N leaching and farm profitability can be inaccurate. Therefore, we apply an integrated modeling approach to link a dynamic stochastic economic model (Section 2.2) with an Agricultural version of the Integrated Biosphere Simulator (Agro-IBIS) model and Terrestrial Hydrologic Model with Biogeochemistry (THMB) (Ferin et al., 2021, 2023) to construct the above conceptual framework and investigate the optimal crop mixes and land use to optimize N leaching and farm profitability.

2.2 Dynamic stochastic economic model

A multi-period recursive stochastic mathematical programming model is developed to determine the optimal land allocation to produce four major annual crops (i.e., corn, soybeans, alfalfa, oats), two perennial crops (miscanthus and switchgrass), cover crop (rye with winter kill termination practice), derived secondary products (i.e., corn stover, corn oil, soybean oil, corn ethanol, distiller's dried grains with solubles), and animal products (i.e., beef, dairy, pork, broiler, eggs) across 166 grids at a resolution of 10 km (or 13 counties) within in the RRB, Iowa. The present model determines the maximum discounted value of the net economic benefits in the agricultural sector over the 2016–2045 period under different agricultural practices (i.e., adoption of perennial crops and cover crop) and N policy scenarios.

To investigate the uncertainty in N reduction, the model applies a chance-constraint method to the N leaching constraint given distinct probabilistic levels the N leaching constraint would be achieved. The resulting outcomes can be interpreted at different probabilistic levels and provide implications regarding the uncertainty in N reduction. The model formulation is detailed in Supporting Information (SI) 1.

We parameterized the model using data from several sources. Crop prices from 2016 to 2021 were retrieved from USDA-NASS. The agricultural production cost data was obtained from Iowa State University Extension and Outreach (2016). Land use and land type data were collected from Cropland Data Layer (CDL)(Boryan et al., 2011), and the marginal land classification was modified from Jiang et al. (2021) (details refer to SI 2). Crop yield and nitrate leaching data were from an Agricultural version of the Integrated Biosphere Simulator (Agro-IBIS) model and Terrestrial Hydrologic Model with Biogeochemistry (THMB) (Ferin et al., 2021, 2023). Because crop yields, yield-dependent production costs, N loads, and land availability vary across 166 grids at the 10 km scale in the RRB Watershed over 2016–2045, the results generated from the mathematical programming model are temporally and spatially heterogeneous.

2.3 Modeling scenarios

Various modeling scenarios are used to investigate the economically optimal crop choice, land use changes, and biomass production across 166 grids at a resolution of 10 km and 13 counties within the Raccoon River Watershed from 2016 to 2045. The modeling scenarios include adoption of cover crop and perennial crops given three biomass price scenarios (i.e., $0, $70, and $100 per Mg of biomass) and three N reduction target scenarios (i.e., no policy, deterministic N reduction target, and 95% stochastic N reduction target). The choice of biomass prices reflects the range of the historical cornstalk price in Iowa (USDA, 2024). The N reduction policy is assumed to linearly reduce N-leaching over 25 years by 20% relative to the 30-year average N-leaching amount. Three N reduction policy scenarios are considered to investigate the effect of the N reduction target on land use change, cover crop and perennial crops adoption, and N leaching with uncertainty. In addition to no N policy scenarios, the deterministic N reduction target doesn't require a probability to meet the N reduction policy, reflecting the outcome without considering the uncertainty. On the other hand, the stochastic N reduction target specifies a probability to achieve the N reduction target, reflecting the outcome with considering the uncertainty. The combination of the considered three biomass price scenarios and three N policy scenarios results in a total of nine sub-scenarios. All the sub-scenarios are run at the 10 km and county scales. Therefore, 18 model runs are conducted.

The baseline scenario, which serves as a reference benchmark to compare with other scenarios, is where the resulting 2016 cover crop adoption rate is close to the observed level in 2016 (CTIC, 2024; Zhou et al., 2022), and there is no adoption of perennial crops and nitrogen reduction target. The cover crop adoption rate is calculated by the amount of land adopting the cover crop practice divided by the total amount of corn and soybean land. The lower bound 2.5% adoption rate is used as an initial adoption rate based on the observed cover crop coverage in 2016 (CTIC, 2024) and calibration result (SI 3).

3. Results

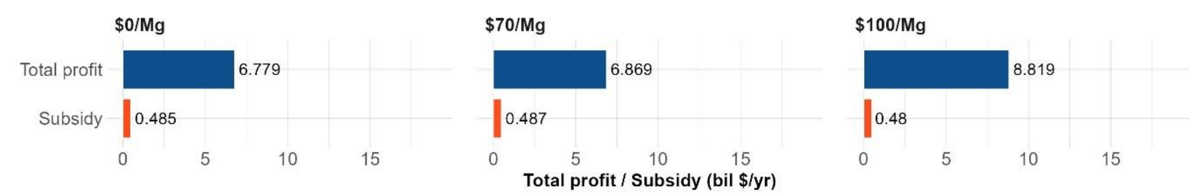
3.1 Effect of cover crop and perennial crop adoption on N leaching, total profits, and land use

The estimated land use results from the dynamic stochastic economic model are validated by CDL data from 2016 to 2021. The validation results in the entire RRB watershed domain show that the difference between estimated corn acreage and observed acreage varies from -9.7% to -10.7% for the 10 km-scale model and from -7.1% to -9.35% for the county-scale model, and the difference in soybean acreage is -7.0% to -7.8% for the 10 km-scale model and -4.6% to -5.5% for the county-scale model. The cover crop adoption acreage in 2016 is calibrated with the satellite data (Zhou et al., 2022), and the calibration results show a difference between estimated and observed cover crop adoption acreage is 5.1% for the 10 km-scale model and 7.8% for the county-scale model. All the dynamic stochastic economic model validation and calibration results are documented in SI 3.

The baseline scenario in this study is when there is no biomass market (i.e., biomass price is \$0 Mg^{-1}), and the cover crop adoption rate is 2.5% in the base year which is aligned with the satellite observed data. The baseline scenario results in 2045 show that the estimated total farm profit is \$6.8 billion with a cover crop subsidy of \$0.5 billion, and the N leaching is 4.8 million kg-N (Figure 2). The corresponding land use allocation presents 0.37 million ha of corn land without the cover crop adoption acreage, 0.02 million ha corn land with the cover crop adoption, and 0.29 million ha of land plated for soybeans (Figure 3a). There is no perennial crop production under the baseline scenario because of \$0 Mg^{-1} biomass price. The most common rotation type is corn-soybean rotation with 30% corn stover removal which accounts for 0.48 million ha (Figure 3b).

With the introduction of the biomass market and the adoption of perennial crops, the total farm profit is expected to be 1.3% and 30.1% higher relative to the baseline scenario when the biomass price is \$70 Mg^{-1} and \$100 Mg^{-1}, respectively (Figure 2). The corresponding corn acreage increases 0.5% and 2% (Figure 3), and N leaching is 3.7% and 11.2% higher. These outcomes indicate that the higher biomass price occurs, the more corn stover production is anticipated, leading to more demand for corn land and, in turn, worsen water quality. For instance, when the biomass price is \$100 Mg^{-1}, producing corn with stover becomes more profitable, so N leaching is higher than in other biomass price scenarios due to the greater presence of corn land (Figure 3a). In addition, the results also show that a higher biomass price incentivizes more idle land to be converted into biomass production (Figure 3a). Cover crop adoption is expected to see more in corn-soybean rotation with a 30% stover removal rate and continuous corn rotation with a 0% stover removal rate (Figure 3b).

a. Total profit and subsidy



b. N leaching

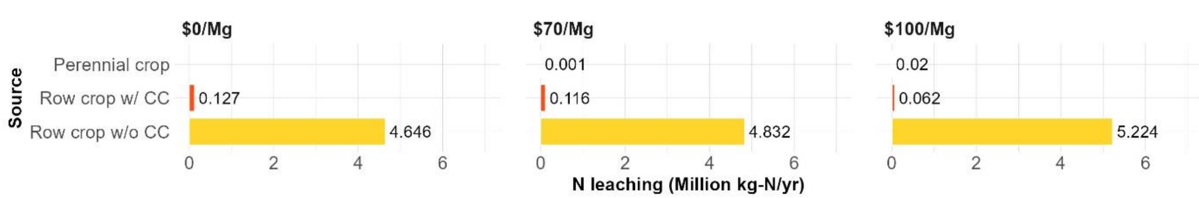
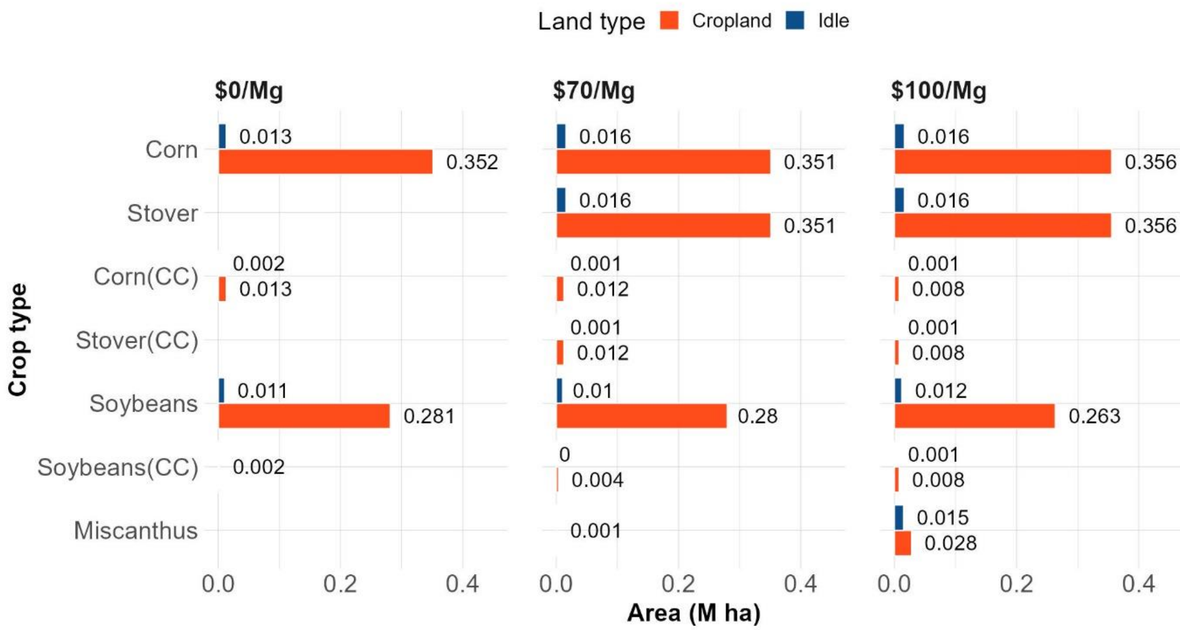


Figure 2. Effect of perennial and cover crop adoption on nutrient loss and total profit in 2045
Note: '(CC)' denotes a rotation with the cover crop practice.

a. Land use change by crop types



b. Land use change by rotation types

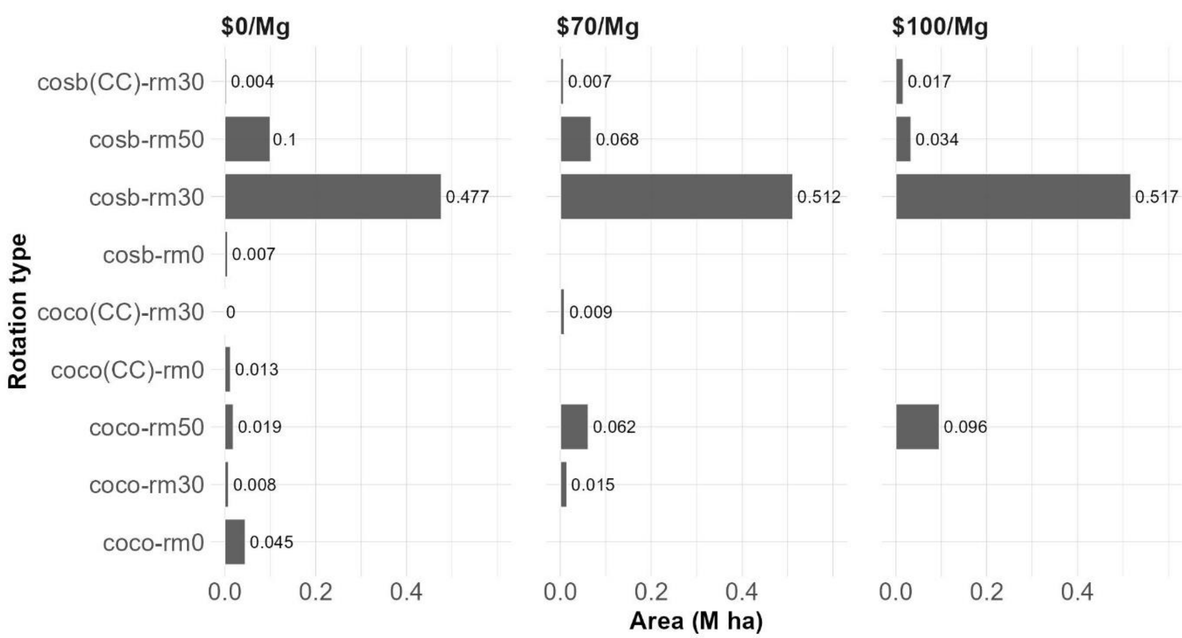
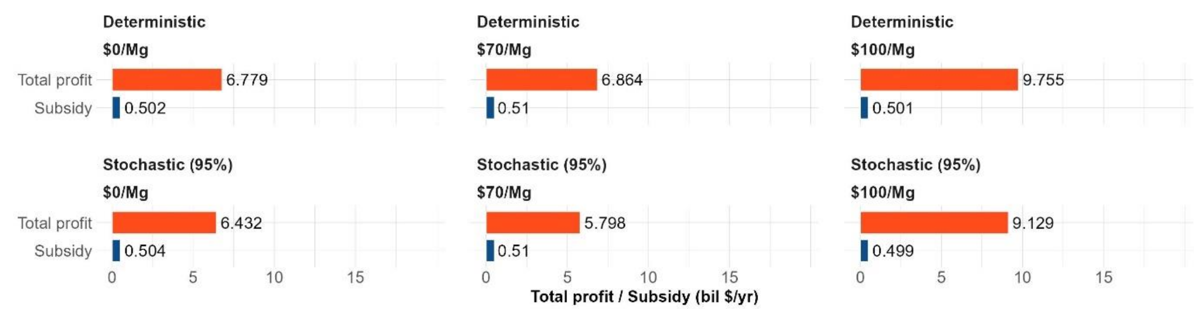


Figure 3. Effect of perennial and cover crop adoption on land use changes in 2045
Note: 'coco' denotes continuous corn rotation; 'cosb' denotes corn-soybean rotation; 'rm' denotes the corn stover removal rate.

3.2 Effect of N reduction policy on N leaching, total profits, and land use

In this section, we examine how the implementation of the N reduction target can affect the adoption of cover crop and perennial crops, land use, N leaching, and total profits. To account for the uncertainty in N loss, in addition to applying the conventional deterministic constraint, we also employ a stochastic constraint to specify the probability of meeting the N reduction target. We use a 95% stochastic constraint, which requires the modeling solution to satisfy the N reduction target at a 95% confidence level so that the resulting model solution has a higher assurance level to mitigate N leaching while minimizing the impact of uncertainty in N loss.

a. Total profit and subsidy



b. N leaching

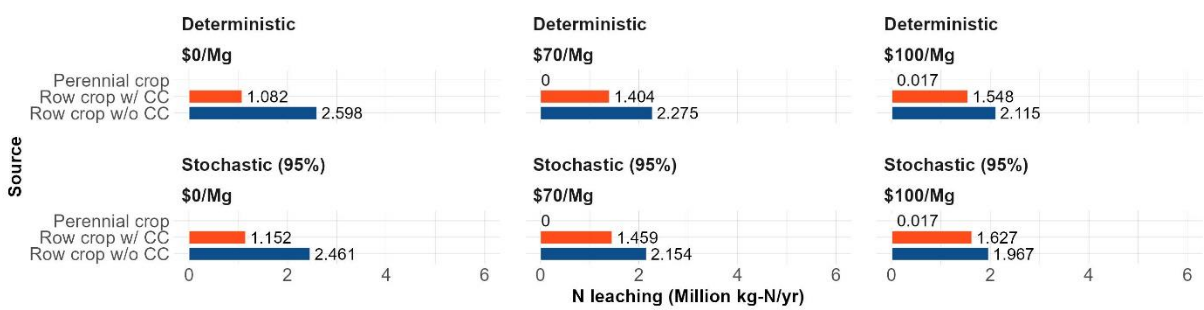


Figure 4. Effect of N reduction policy on nutrient loss and total profit in 2045

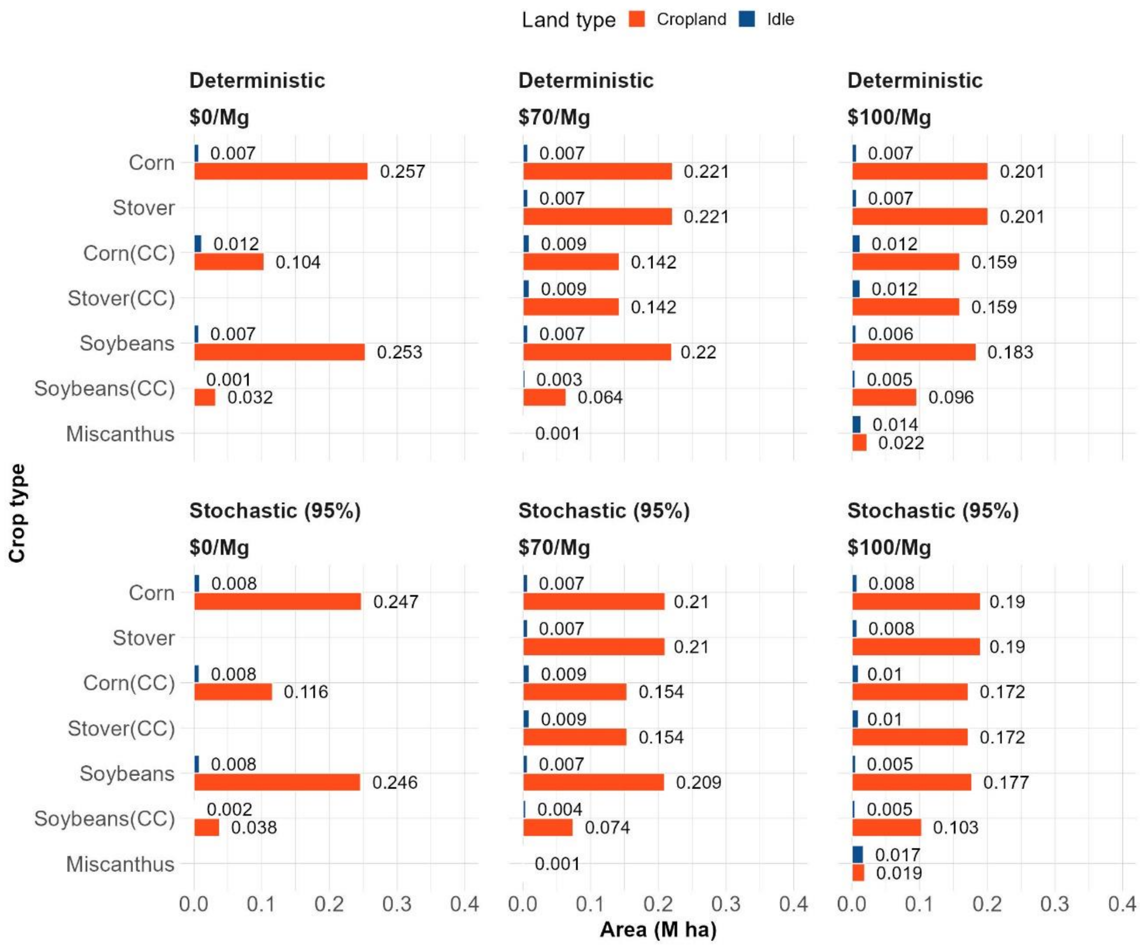


Figure 5. Effect of N reduction policy on land use changes in 2045

The stochastic results tend to have lower total profits (Figure 4a), lower N leaching from row crops without the cover crop adoption, and higher N leaching from row crops with the cover crop adoption (Figure 4b) compared to the deterministic results due to less corn land in production under the 95% stochastic scenarios (Figure 5). The results also show that implementing the N reduction target facilitates more cover crop adoption than the scenarios without the N reduction target (refer to Figure 5 and Figure 3a). Under the 95% stochastic scenarios, there is less corn land without the cover crop adoption than the deterministic scenarios, indicating that less corn production without the cover crop adoption is expected to occur when the model aims to consider the uncertainty in N loss and requires a higher assurance level to meet the N reduction target. On the other hand, more corn land with the cover crop adoption is expected to occur under the 95% stochastic scenarios relative to the deterministic scenarios (Figure 5), due to the benefit of the cover crop adoption to nutrient losses.

Various biomass prices and the implementation of the N reduction target can affect distinct crop mixes, cover crop/perennial crop adoption, and N-leaching spatial patterns. Figure 6 shows that under the baseline scenario (i.e., biomass price is \$0 Mg^{-1} and no N policy), more corn land without the cover crop adoption is estimated over the entire RRB watershed in 2045. The central and southern RRB watershed will have relatively high N loses (Figure 6a), which is aligned with the spatial distribution of N leaching rate in each 10-km grid (Figure S11). There is no miscanthus production because the biomass price is \$0 Mg^{-1}. When the biomass price is \$70 Mg^{-1}, part of corn land without the cover crop adoption is expected to be replaced with miscanthus (Figure 6b). When the biomass price increases to \$100 Mg^{-1}, more miscanthus is expected to be planted over the RRB watershed. Nevertheless, more miscanthus production doesn't necessarily lead to lower N leaching. In the absence of the N reduction policy under the \$100 Mg^{-1} biomass price scenario, the southern RRB watershed has a higher N loss relative to \$0 Mg^{-1}, indicating that a higher biomass price incentivizes not only miscanthus production but also corn stover production so that more corn land demand is expected. In the presence of the N reduction policy given various biomass prices, more cover crop corn land occurs mainly in the center and south of the RRB watershed and replaces the corn land without the cover crop adoption, and a more significant reduction in the corresponding N loss is expected in the east and southeast of the RRB watershed. The above results suggest that biomass prices and the N reduction target can induce distinct crop mixes and spatially varying patterns of cover crop and perennial crop adoption.

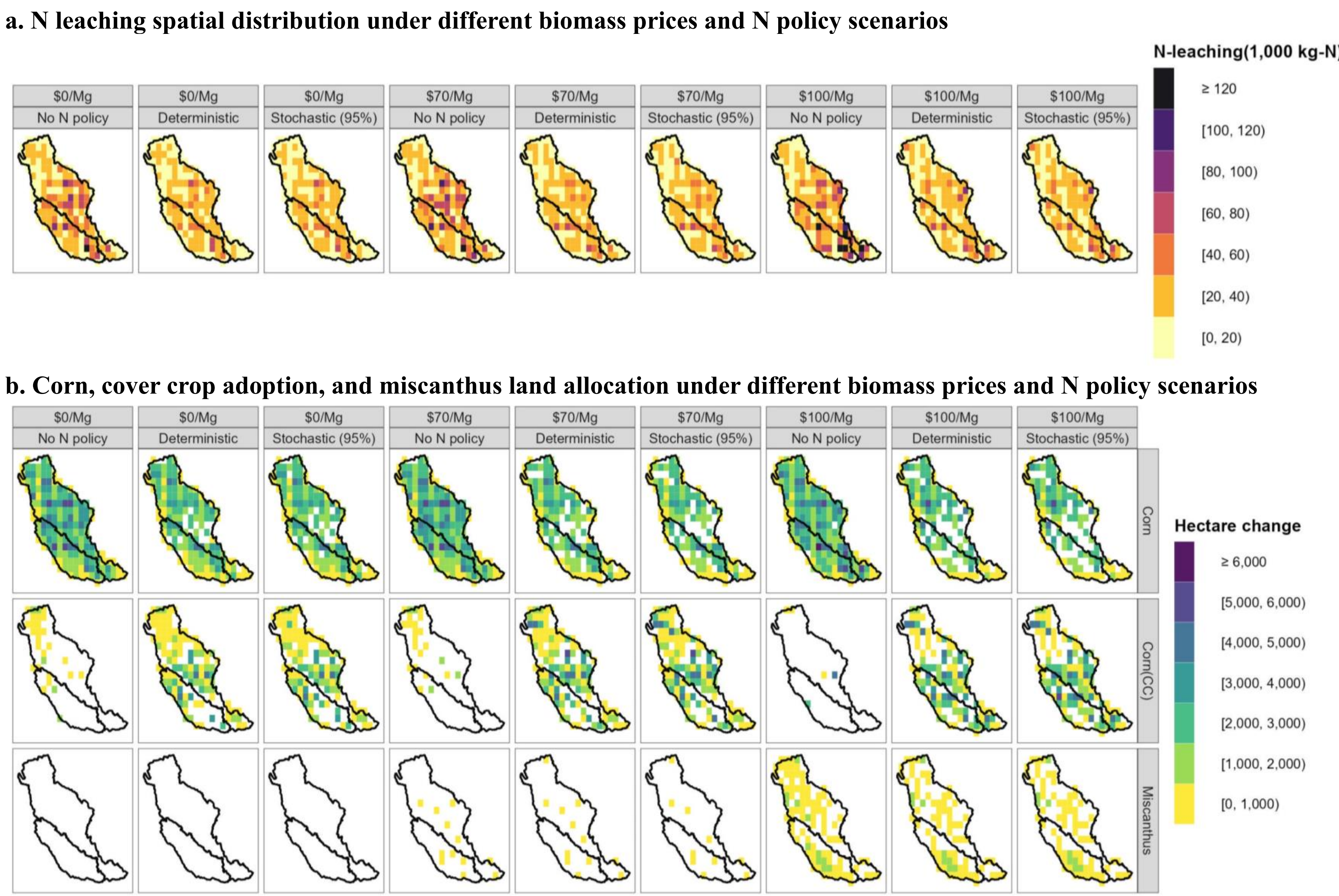


Figure 6. Spatial distribution of N leaching and corresponding crop mix of interest in 2045

Part a of Table 2 shows changes in cover crop adoption rate under various biomass price and N reduction constraint scenarios at the end of the modeling year (2045). The results show that when no N reduction policy exists, the cover crop adoption rate stays at the observed cover crop adoption rate in the RRB in 2016 (2.5%). The cover crop adoption rate in 2045 increases to 22.1% to 40.7%, depending on the biomass price, under the deterministic N reduction constraint scenarios, indicating that the N reduction target policy can promote the cover crop adoption rate. Considering uncertainty in N loss, the stochastic constraint requiring a higher assurance level of reducing N leaching leads to an even higher cover crop adoption rate (24.3% to 43.2%) relative to the deterministic scenarios.

Table 2. Estimated cover crop adoption rates and N abatement cost in 2045

N policy constraint	**\$0 Mg^{-1}**	**\$70 Mg^{-1}**	**\$100 Mg^{-1}**
a. Estimated cover crop adoption rates (% of the total corn and soybean land)			
No N constraint	2.50	2.50	2.50
Deterministic	22.05	32.45	40.67
Stochastic (95%)	24.27	35.82	43.21
b. N abatement cost (\$/kg- N)			
Deterministic	1.58	1.99	2.69
Stochastic (95%)	1.57	1.98	2.45

Unit: % of the total corn and soybean land

Note that although Part a of Table 2 shows that a higher biomass price leads to a higher cover crop adoption rate, a higher biomass price, in fact, results in lower cover crop adoption in actual hectares (Figure 2a). There are two factors that can increase the cover crop adoption rate by definition: one is increasing the amount of land adopting the cover crop practice; the second is decreasing the amount of total land in corn and soybean production. The higher biomass price induces more land initially used for row crop production to be converted into perennial crop production. Therefore, when the land with the cover crop practice doesn't change much with decreasing total corn and soybean production land, the cover crop adoption rate can seem higher.

The N abatement costs under various scenarios are estimated from the dynamic and stochastic mathematical programming model (Part b of Table 2). The results show that when there is no biomass market (i.e., biomass price is $0/Mg), the N abatement cost is estimated to be lower under the stochastic scenarios than the deterministic scenarios because the stochastic scenarios require a higher assurance to reduce N leaching, resulting lower N leaching. Moreover, the higher the biomass price incurs, the higher the N abatement cost would be anticipated, reflecting the opportunity cost of replacing corn land, which has higher profits when the biomass price is high due to the stover production.

3.3 Difference in results between 10 km- and county-scale models

Table 3 summarizes the difference in key results estimated from 10 km- and county-scale models, and the county-scale model results are documented in SI 4. The difference rate is calculated relative to the country-level results. The difference in the estimated total farm profits in the RRB watershed in 2045 shows that the estimated total farm profits from the 10 km-scale model tend to be lower relative to the county-scale model, while the 10 km-scale model has higher estimated N leaching in 2045 compared to county-scale model results.

The reasons for those differences between models at two different scales is that each county in the RRB watershed includes multiple 10 km scale grids, and crop yields and N leaching values vary across the covered grids. To construct the county-scale model, each county only has one single crop yield value (i.e., a simple average of crop yield values from the covered grids), which cannot fully reflect the crop yield heterogeneity and spatial distribution across all grids. Specifically, the distribution of crop yield from 10 km grids in each county is left-skewed, implying that there are only a few observations with lower crop yield values and most of the observations with higher crop yield values. The left-skewed distribution leads to a simple average of crop yields from the covered grids closer to the upper bound of yield distribution (refer to SI 5). Therefore, the county-scale model has a higher representative crop yield value relative to the 10 km-scale model, resulting in higher total farm profits.

Similarly, the N leaching has the same issue but with a right-skewed distribution, meaning most of the observations have relatively low N leaching values, and only a handful of observations have high N leaching values. Thus, the county-scale model tends to have lower representative N leaching values (i.e., simple average of N leaching values from the covered 10 km grids within each county) than the 10 km scale model, inducing the estimated N leaching results from the county-scale model are lower than the 10 km-scale model.

Table 3. Percentage differences in 10 km-scale results relative to county-scale results in 2045

Variable	**N policy constraint**	**\$0 Mg^{-1}**	**\$70 Mg^{-1}**	**\$100 Mg^{-1}**
Total profits	No N policy	-2.24	-1.96	-13.67
	Deterministic	-2.21	-1.96	-4.05
	Stochastic (95%)	-7.07	-9.18	18.28
Cover crop subsidy	No N policy	0.21	0.41	0.42
	Deterministic	0	0.99	1.01
	Stochastic (95%)	-1.95	-0.78	-0.2
N leaching	No N policy	2.77	2.72	6.65
	Deterministic	0	0	0
	Stochastic (95%)	5.52	5.41	5.21

Unit: % change relative to modeling result at a county-level.

4. Discussion

Uncertainty in N loss can affect the effectiveness of N leaching reduction strategies. To account for the uncertainty in N loss, this study applies the chance-constraint optimization model to specify the probability of achieving the desired level of N target load. Other study employed a similar approach but with a multi-objective optimization model and found that securing nutrient loads with higher levels of resilience is more costly (Rabotyagov et al. 2016). This finding is aligned with our findings in total profit losses. Figure 4 shows that total profit losses estimated from the deterministic model given different biomass prices are 5% to 16% higher than the stochastic model, indicating that the higher assurance of reducing N leaching requires more stringent N reduction target load and is expected to induce greater losses in total profits. The implication of this finding from the present study and Rabotyagov et al. (2016) is that the total profit loss due to the implementation of N reduction practices or policies is likely underestimated if the uncertainty in N loss is not considered. Moreover, the higher assurance of reducing N leaching can reduce N loss, while the farm profitability is expected to decline due to requiring a more stringent N reduction target load. Similarly, Burkart & Jha (2007) investigated the effect of implementing a nonpoint source trading scheme and showed that the total farm watershed loss is anticipated to be larger under a less-permit scenario (i.e., more stringent scenario) than under a more-permit scenario (i.e., less stringent scenario), implying a tradeoff between N leaching and farm profitability.

The biomass price plays a vital role in determining crop mix, biomass production, and N leaching. A higher biomass price can induce more perennial crop production and corn stover production. However, these two biomass sources have distinct implications to N leaching. Biomass supply from corn residues can worsen nutrient loss, and biomass from perennial crop production can curtail N loss (Egbendewe-Mondzozo et al., 2011). Nevertheless, if perennial crop production takes place on idle land, then the benefit of reducing N loss via the perennial crop adoption becomes limited because the main sources of N leaching from corn land remain in production (Valcu-Lisman et al., 2016). This result is also found in this study showing that a higher biomass price without any N reduction policy leads to higher N leaching (Figure 2b). Therefore, the implementation of N loss reduction target is suggested as an effective approach to induce displacement of N-intensive row crop with other energy crops (Ferin et al., 2021). The findings of the present study also support this point of view and show that the implementation of the N reduction target facilitates the displacement from corn land to perennial crop adoption. Without the N reduction target, the displacement of N-intensive row crop is less significant and largely determined by the biomass price. Note that although the displacement of corn land is mainly replaced by miscanthus in this study, our model does consider switchgrass as a perennial crop option. However, adopting switchgrass is not profitable given the current biomass price scenarios in this study. Existing study shows that landowners would be more likely to plant switchgrass when the biomass price ranges from \$113 Mg^{-1} to \$176 Mg^{-1} (Chen et al., 2021).

5. Conclusions

The aim of this research is to examine how adopting a cover crop on existing land use improves N leaching and how incorporating perennial crops given different biomass prices affects land use change, N leaching, and total farm profits. This study applies the stochastic modeling approach to account for uncertainty in N reduction and uses both grid- and county-scale data to examine differences in the estimated land use changes, N leaching, and total farm profits at different data scales.

The results of this study show that a high biomass price can induce more perennial crop production and corn stover production, so the introduction of the perennial crop alone without the

N reduction target may not be sufficient to reduce N losses. The interaction effect of adopting cover crop and perennial crops with the implementation of the N leaching reduction target on land use change and N leaching indicates that the implementation of the N reduction target is anticipated to incentivize the adoption of cover and perennial crops, promote the utilization of marginal land, and result in a lower N leaching. In scenarios where policymakers prioritize reducing uncertainty in N loss and require a higher assurance level to curtail N leaching, a decrease in corn production is expected to occur and a higher estimated N abatement cost, leading to diminished N leaching but greater losses in total farm profits.

The implications of these results suggest that the cover crop adoption can curtail N leaching, while a high biomass price can incentivize more corn stover production, in turn, more demand for corn land. Thus, the effectiveness of the cover crop practice on the N leaching reduction can also be partially offset by a relatively high biomass price (e.g., \$100 Mg-1) because more corn production is expected to occur to produce corn stover. Therefore, in addition to promoting the adoption of cover crop and perennial crop alone, the implementation of the N reduction target policy can be an effective approach to ensure the overall land use allocation is toward the pathway to decreasing N leaching. The findings of this study provide insights into how adopting cover crop on the existing land use can reduce N leaching with a relatively low cost in terms of cover crop subsidy expenses, and how adopting perennial crops can alter land use change, N leaching, and total farm profits. All the results in this study are investigated at grid- and county-scale, respectively. The comparison of the estimated results between two distinct modeling granularities shows that, overall, the results from both models have similar patterns with $\pm$20% differences in magnitudes depending on the skewness of data distribution (Section 3.3 and SI 5).

This watershed-based study provides valuable insight into nutrient loss management and the associated implications to land use changes and regional economy. While the external validation of this study may be limited due to a small-closed economy assumption, where the price changes in the small watershed won’t affect the market prices in a larger economy scale. For instance, the biomass price would be affected by widespread adoption of perennial crops in a larger scope, and the resulting massive supply would decrease the market price. This indirect feedback loop is not captured in a relatively small watershed-based study. Continued efforts are needed to consider price changes on a larger economic scale.

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Supporting Information

SI 1. Stochastic and dynamic mathematical programming model

Since the perennial crop lasts multiple years unlike annual crops, the model is solved in multiple recursive iterations with considering terminal value of perennial crops at the end of the modeling year. Specifically, decisions made in year t account for potential profit over the following nine years (t to t+9), assuming perennial crops have a lifetime of ten years. Once the first iteration (i.e., t to t+9) is completed, the model obtains the optimal land use allocation and crop mix in year t based on the outcome of the maximum profits incurred over t to t+9. Next, the model starts a new iteration (t+1 to t+10) given the optimal land allocation, land rent, and profits of each crop determined in the previous iteration. The crop yield growth rate is assumed to be 2% every year. The illustration of the above decision-making process is shown in Figure S1. The next sub-section describes the formulation of the mathematical programming model, consisting of a profit maximization objective function and a set of constraints and being solved in every recursive iteration.

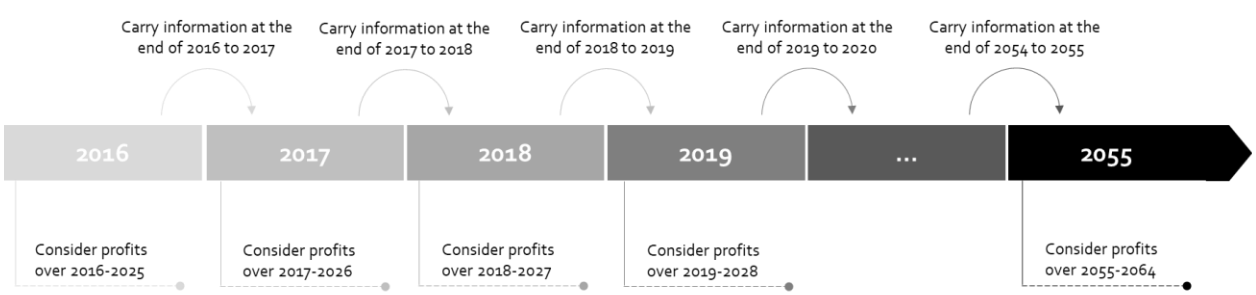

Figure S1. Recursive decision-making process.

Table S1. Mathematical notation description: subscripts, variables, and function

Notations	Definition
Subscripts	
$\boldsymbol{t}$	Recursive planning period in each iteration
$\boldsymbol{c}$	Grid cell (at the 10 km scale)
$\boldsymbol{i}$	Primary crop products (corn, soybeans, alfalfa, oats)
$\boldsymbol{j}$	Processed products (corn oil, ddg, and soybean oil)
$\boldsymbol{k}$	Primary livestock products
$\boldsymbol{z}$	A product vector $z = (i, j)$
$\boldsymbol{l}$	Merchantable livestock products
$\boldsymbol{r}$	Rotation type (coco, cosb, alfa-alfa, oat-oat)
$\boldsymbol{n}$	Tillage type (no tillage, conventional tillage)
$\boldsymbol{v}$	Corn stover removal rate (0, 30%, 50%)
$\boldsymbol{d}$	Land type
$\boldsymbol{a}$	Age of perennial crops
$\boldsymbol{f}$	Fertilizer type (N, P, K)
$\boldsymbol{p}$	Perennial crop type (miscanthus, switchgrass)
$\boldsymbol{g}$	Grazing land type
$\boldsymbol{m}$	Animal group type
$\boldsymbol{u}$	Nutrition type required for livestock activities
Variables	
$\boldsymbol{PRIMARY_{i,c,t}}$	Primary row crop i produced in cell c in year t (Unit: bushel for corn\soybean\oats; ton for alfalfa)
$\boldsymbol{QCE_t}$	The amount of corn ethanol produced in year t (gal)
$\boldsymbol{QDSL_{j,t}}$	The amount of biodiesel produced from processed products j in year t (gal)
$\boldsymbol{BMASS_{c,t}}$	The amount of total biomass production in cell c in year t (ton)
$\boldsymbol{LS_{k,t}}$	The quantity of livestock product k produced in year t (animal unit)
$\boldsymbol{RPLANT_{r,n,v,d,c,t}}$	Land allocated for rotation r with tillage method n and removal rate v on land type d in cell c in year t (acre)
$\boldsymbol{PPLANT_{p,a,d,c,t}}$	Land allocated to plant perennial crop p at age a on land type d in cell c in year t (acre)
$\boldsymbol{CSPLANT_{r,n,v,d,c,t}}$	Land allocated for corn stover production in rotation r with tillage method n and removal rate v on land type d in cell c in year t (acre)
$\boldsymbol{PROCESS_{i,t}}$	The quantity of row crop i processed in year t (bu)
$\boldsymbol{RAC_{i,d,c,t}}$	Row crop production by row crop i on land type d in cell c in year t (acre)
$\boldsymbol{PAC_{p,d,c,t}}$	Perennial crop production by perennial crop p on land type d in cell c in year t (acre)
$\boldsymbol{W_{c,t}} \in [\boldsymbol{0}, \boldsymbol{1}]$	The weight based on historical crop mixes assigned in cell c in year t
$\boldsymbol{HW_{c,t}} \in [\boldsymbol{0}, \boldsymbol{1}]$	The weight based on hypothetical crop mixes assigned in cell c in year t
$\boldsymbol{WW_t} \in [\boldsymbol{0}, \boldsymbol{1}]$	The weight based on historical crop mixes assigned at the entire watershed domain in year t
$\boldsymbol{HWW_t} \in [\boldsymbol{0}, \boldsymbol{1}]$	The weight based on hypothetical crop mixes assigned at the entire watershed domain in year t
$\boldsymbol{UNUSEDAC_{d,c,t}}$	The amount of unused cropland on land type d in cell c in year t (acre)
$\boldsymbol{SUPPLY_{i,c,t}}$	The total supply of row crop i in cell c in year t (bushel for all crops except for alfalfa in ton)
$\boldsymbol{FD_{z=\{i,j\},k,t}}$	The amount of primary crop product i or processed product j for producing livestock product k in year t
$\boldsymbol{QOIL_{j,t}}$	The amount of oil-related products produced from processed products j in year t
$\boldsymbol{BMASSCS_{d,c,t}}$	The amount of biomass produced from corn stover on land type d in cell c in year t (ton)
$\boldsymbol{NUTR_{u,k,t}}$	The amount of nutrition u needed per livestock product k in year t
$\boldsymbol{NLEACH_{c,t}}$	N leaching in cell c in year t (kg of N)
Function	
$\boldsymbol{1}[\cdot]$	Indicator function, which is 1 if the condition described in $[\cdot]$ is met, and 0 otherwise.

Note: * denotes the unit of the corresponding variable varies by different types of products.

Table S2. Mathematical notation description: parameters

Notations	Definition
Parameters	
$\boldsymbol{T}$	Planning period length (10 years)
$\boldsymbol{\pi}$	Social discount rate (3%)
$\boldsymbol{rp_i}$	Average market price of row crop i over 2016-2021 ($/*)
$\boldsymbol{cep}$	Corn ethanol price ($/gal)
$\boldsymbol{bdslp}$	Market price of biodiesel ($/gal)
$\boldsymbol{bp_s}$	Biomass price under s scenario ($/ton)
$\boldsymbol{lsp_{k,t}}$	Market price of livestock product k in year t ($/animal unit)
$\boldsymbol{ccp}$	Cover crop incentive payment ($/acre)(Table S3)
$\boldsymbol{ry_{i,r,n,v,c,t}}$	Yield of row crop i produced in rotation r with tillage method n and removal rate v in cell c in year t (*/acre)
$\boldsymbol{rpc_{i,r,n}}$	Production variable cost (excluding fertilizer cost) for row crop i in rotation r with tillage method n ($/yield)
$\boldsymbol{fc_{i,r,n,f}}$	Cost of applying fertilizer f for row crop i in rotation r with tillage method n in cell c ($/lb)
$\boldsymbol{npk_{i,r,n,f,v,c}}$	Application rate of fertilizer f for row crop i in rotation r with tillage method n and removal rate v in cell c (lbs/yield)
$\boldsymbol{nfr}$	Cost saving from nitrogen fertilizer reduction due to the cover crop practice ($/lb)(Table S3)
$\boldsymbol{rfc_{i,r,n}}$	Production fixed cost of row crop i in rotation r with tillage method n ($/acre)
$\boldsymbol{ccs}$	Cover crop saving from erosion/weed reduction ($/acre)(Table S3)
$\boldsymbol{ppc_{p,c}}$	Production cost of perennial crop p in cell c ($/acre)
$\boldsymbol{py_{p,c}}$	Yield of perennial crop p per acre in cell c (ton/acre)
$\boldsymbol{pfc}$	Cost of applying Nitrogen fertilizer for perennial crops ($/acre)
$\boldsymbol{lcc_c}$	Land conversion cost for marginal land to produce crops in cell c ($/acre)
$\boldsymbol{lrc_{d,c,t}}$	Land rent cost for land type d in cell c in year t ($/acre)
$\boldsymbol{cs}$	Production cost of corn stover ($/*)
$\boldsymbol{psc_i}$	Processing cost of row crop i ($/bu)
$\boldsymbol{cnc_t}$	Production cost (including refinery processing, transportation, tax) for corn ethanol in year t ($/gal)
$\boldsymbol{lpc_k}$	Production cost of primary livestock k ($/animal unit)
$\boldsymbol{v_{p,c}}$	Value of the remaining life of standing perennial crop p in cell c beyond the planning period T ($/ton)
$\boldsymbol{w_{p,c}}$	Opportunity cost for alternative land use except for perennial crop p in cell c beyond the planning period T ($/ton)
$\boldsymbol{al_{d,c}}$	Available land by land type d in cell c (acre)
$\boldsymbol{ccar}$	Cover crop adoption rate (% of the total corn and soybeans land)
$\boldsymbol{h_{i,c,t}}$	Historically observed acreage patterns for row crop i in cell c in year t (acre)
$\boldsymbol{\hat{h}_{i,c,t}}$	Hypothetical acreage patterns for row crop i in cell c in year t (acre)
$\boldsymbol{hw_{i,t}}$	Historically observed acreage patterns for row crop i at the entire watershed domain in year t (acre)
$\boldsymbol{\widehat{hw}_{i,t}}$	Hypothetical acreage patterns for row crop i at the entire watershed domain in year t (acre)
$\boldsymbol{ddg2dsl}$	Conversion rate of producing diesel from DDG
$\boldsymbol{oil2dsl_{i,j}}$	Conversion rate of producing diesel from processed product j (gallon/ton)
$\boldsymbol{eth2ddg}$	Conversion rate of producing DDG from corn ethanol (ton/gallon)
$\boldsymbol{raw2pro_{i,j}}$	Conversion rate of producing processed product j from row crop i (ton/bushel)
$\boldsymbol{corn2eth}$	Conversion rate of producing corn ethanol from corn (gallon/bushel)
$\boldsymbol{csy_{r,n,v,c,t}}$	Yield of biomass produced from corn stover in rotation r with tillage method n and removal rate v in cell c in year t (ton/acre)
$\boldsymbol{as_{m,k}}$	Share of livestock product k in each animal group m
$\boldsymbol{\lambda_{g,c}}$	The amount of forage required per animal unit per acre of grazing land g in cell c (animal unit/acres)
$\boldsymbol{nr_{an,u}}$	Required amount of nutrition u per animal an (*/100lbs)
$\boldsymbol{fwc_{z=\{i,j\}}}$	Feed weight conversion rate from primary crop product i and processed product j
$\boldsymbol{re_{z=\{i,j\},u}}$	Nutrition u contented in primary crop product i or in processed product j
$\boldsymbol{ddgwl_k}$	DDG weight limit for producing primary livestock product k
$\boldsymbol{\delta_t}$	Existing corn ethanol target mandate in year t (gallon/year)
$\boldsymbol{rnlr_{r,n,v,c,t}}$	N leaching rate for rotation r with tillage method n and removal rate v in cell c in cell c in year t
$\boldsymbol{pnlr_{p,c,t}}$	N leaching rate for land allocated to perennial crop p in cell c in year t
$\boldsymbol{de_{c,t}}$	N delivery efficiency in cell c in year t
$\boldsymbol{nl_t}$	N leaching limit in cell c in year t (kg of N per year)

SI 1.1 Objective function

The objective function, including revenues, production costs, and transportation costs, land conversion costs, and terminal perennial crop values, can be expressed as below:

$$Max \sum_{t=0}^{T} e^{-\pi t} \left\{ \sum_{i,c} rp_i \cdot PRIMARY_{i,c,t} \right.$$

↪ Sum of revenues from row crops directly selling to the market

$$+cep \cdot QCE_t$$

↪ Sum of revenues from corn ethanol

$$+\sum_{j} bdslp \cdot QDSL_{j,t}$$

↪ Sum of revenues from biodiesel

$$+bp \cdot BMASS_{c,t}$$

↪ Sum of revenues from biomass

$$+\sum_{k} lsp_{k,t} \cdot LS_{k,t}$$

↪ Sum of revenues from the livestock products

$$+\sum_{l,c} ccp \cdot 1[CC] \cdot RPLANT_{r,n,v,d,c,t}$$

↪ Subsidy revenue from cover crop incentive payments

$$-\sum_{f,r,n,v,c} \left[ry_{i,r,n,v,c,t} \ \left(rpc_{i,r,n} + fc_{i,r,n,f} \cdot \left(npk_{i,r,n,f,v,c} - nfr \cdot 1[CC] \right) \right) + rfc_{i,r,n} - ccs \right.$$
$$\left. \cdot 1[CC] \right] \cdot RPLANT_{r,n,v,d,c,t}$$

↪ Production costs of row crops

$$-\sum_{p,a,d,c} \left(ppc_{p,c} \cdot py_{p,c} + pfc \right) \cdot PPLANT_{p,a,d,c,t}$$

↪ Production costs of perennial crops

$$-\sum_{p,a,d,c} lcc_c\left(RPLANT_{r,n,v,d,c,t} + PPLANT_{p,a,d,c,t}\right)$$

↪ Land conversion costs of marginal land for producing row and perennial crops

$$-\sum_{r,n,p,a,d,c} lrc_{d,c,t}(RPLANT_{r,n,v,d,c,t} + PPLANT_{p,a,d,c,t})$$

↪ Land rent costs for planting row crops and perennial crops

$$-\sum_{r,n,c} cs \cdot CSPLANT_{r,n,v,d,c,t}$$

↪ Production costs of corn stover

$$-\sum_{i,c} psc_i \cdot PROCESS_{i,c,t}$$

↪ Processing costs of primary crop

$$-cnc_t \cdot QCE_t$$

↪ Production costs for producing corn ethanol

$$-cnc_t \cdot QDSL_{j,t}$$

↪ Production costs for producing corn ethanol

$$-\sum_{k} lpc_k LS_{t,k}\Big\}$$

↪ Production costs of livestock products

$$+e^{-\pi T}\sum_{p,a,d,c}\left(v_{p,c} - w_{p,c}\right)PPLANT_{p,a,d,c,t=T} \qquad Eq.(1.1)$$

↪ The economic value of the remaining life of standing perennial grasses beyond the planning period T

SI 1.2 Constraints

SI 1.2.1 Land use constraints

The balance constraint between total row crop production and total planted area by distinct framing practices on different land types:

$$RAC_{i,d,c,t} = \sum\nolimits_{r,n,v} RPLANT_{r,n,v,d,c,t} \quad \forall q,d,c,t \quad Eq. (1.2)$$

$Eq. (1.3)$ ensures the total land allocated to produce corn stover don't exceed the total corn land.

$$CSPLANT_{r,n,v,d,c,t} \leq RPLANT_{r,n,v,d,c,t} \quad \forall r = \{cosb, coco, cosbCC, cocoCC\}, n, v, d, c, t \quad Eq. (1.3)$$

$Eq. (1.4)$ is the balance constraint for total perennial crop production and total planted area by distinct perennial crop p with age a on land type d in cell c in year t.

$$PAC_{p,d,c,t} = \sum\nolimits_{a} PPLANT_{p,a,d,c,t} \quad \forall p,d,c,t \quad Eq. (1.4)$$

$Eq. (1.5)$ is the balance constraint for current, existing, and new perennial crop p by age a on land type d in cell c in year t.

$$PPLANT_{p,a,d,c,t} = PPLANT_{p,a>2,d,c,t=1} + PPLANT_{p,a=1,d,c,t=1} + PPLANT_{p,a>1,d,c,t>1} \quad \forall p,a,d,c,t \quad Eq. (1.5)$$

$Eq. (1.6)$ ensures the total land allocated to row crops and perennial crops don't go beyond the total available arable land.

$$\sum\nolimits_{r,n,v,d} RPLANT_{r,n,v,d,c,t} + \sum\nolimits_{p,a,d} PPLANT_{p,a,d,c,t} \leq \sum\nolimits_{d} al_{d=\{cropland,idle\},c} \quad \forall c,t \quad Eq. (1.6)$$

where $RPLANT_{r,n,v,d,c,t}$ is the land allocated for rotation r with tillage method n and removal rate v on land type d in cell c in year t. $PPLANT_{p,a,d,c,t}$ is the land allocated to plant perennial crop p at age a on land type d in cell c in year t. $al_{d,c}$ is the total available land in cell c.

$Eq.$ (1.7) restricts the total perennial crop production is not larger than the 25% of the total arable land in year t.

$$\sum_{p,a,d,c} PAC_{p,a,d,c,t} \leq 0.25 \cdot \sum_{d,c} al_{d=\{cropland,idle\},c} \quad \forall t \quad Eq.(1.7)$$

$Eq.$ (1.8) reflects the existing situation where the row crop production with the no-tillage practice is no more than 18% of the total arable land in year t.

$$\sum_{r,n,v,d,c} RPLANT_{r,n=\{no\ til\},v,d,c,t} \leq 0.18 \cdot \sum_{d,c} al_{d=\{cropland,idle\},c} \quad \forall t \quad Eq.(1.8)$$

$Eq.$ (1.9) ensures the cover crop adoption rate is not less than the required adoption rate in year t.

$$\sum_{r,n,v,d} RPLANT_{r=\{osbCC,cocoCC\},n,v,d,c,t} \geq ccar \cdot \sum_{d} RPLANT_{r=\{cosb,coco,cosbCC,cocoCC\},n,v,d,c,t} \quad \forall t \quad Eq.(1.9)$$

$Eq.$ (1.10) and $Eq.$ (1.11) together prevent unrealistic and extreme changes in crop mixes and land use by constructing a convex combination of historically observed acreage patterns ($h_{i,c,t}$) and hypothetical acreage patterns ($\hat{h}_{i,c,t}$)(Chen & Önal, 2012) for each row crop i in cell c in year t.

$$\sum_{d} RAC_{i,d,c,t} = h_{i,c,t} W_{c,t} + \hat{h}_{i,c,t} HW_{c,t} \quad \forall i,c,t \quad Eq.(1.10)$$

$$W_{c,t} + HW_{c,t} \leq 1 \quad \forall c,t \quad Eq.(1.11)$$

where $W_{c,t}$ and $HW_{c,t}$ are the weights based on historical crop mixes and hypothetical crop mixes assigned in cell c in year t, respectively. The sum of the endogenous weights assigned to each cell c in year t must be less than or equal to 1 (convexity requirement), as shown in $Eq. (1.11)$. Similarly, $Eq. (1.12)$ and $Eq. (1.13)$ together prevent unrealistic and extreme changes in crop mixes and land use for each row crop i at the entire watershed domain in year t.

$$\sum_{c,d} RAC_{i,d,c,t} = hw_{i,t}WW_t + \widehat{hw}_{i,t}HWW_t \quad \forall i,t \quad Eq. (1.12)$$

$$WW_t + HWW_t \leq 1 \quad \forall t \quad Eq. (1.13)$$

where WW_t and HWW_t are the weights based on historical crop mixes and hypothetical crop mixes assigned at the entire watershed domain in year t, respectively.

The cropland availability constraint in cell c in year t:

$$\sum_{r,n,v,d=\{cropland\}} RPLANT_{r,n,v,d,c,t} + \sum_{p,a,d=\{cropland\}} PPLANT_{p,a,d,c,t} + UNUSEDAC_{d=\{cropland\},c,t} = al_{d=\{cropland\},c} \quad \forall c,t \quad Eq. (1.14)$$

The idle land balance constraint which adjusts un-used cropland to be idle land in cell c in year t:

$$\sum_{r,n,v,d=\{idle\}} RPLANT_{r,n,v,d,c,t} + \sum_{p,a,d=\{idle\}} PPLANT_{p,a,d,c,t} + UNUSEDAC_{d=\{idle\},c,t} = \sum_{d} al_{d=\{idle\},c} + UNUSEDAC_{d=\{cropland\},c,t} \quad \forall c,t \quad Eq. (1.15)$$

SI 1.2.2 Primary product balance constraints

The balance of the total product supply

$$SUPPLY_{i,c,t} = \sum_{r,n,v,d=\{cropland\}} ry_{i,r,n,v,c,t} \cdot RPLANT_{r,n,v,d,c,t} \quad \forall i,c,t \quad Eq. (1.16)$$

The balance between the total production supply and processed products

$$PROCESS_{i=\{corn,soybeans\},t} + \sum\nolimits_k FD_{z=\{corn,soybeans\},k,t}$$

$$\leq SUPPLY_{i=\{corn,soybeans\},c,t} \;\; \forall i,c,t \quad Eq.(1.17)$$

The balance between the total production supply and primary products sold to the market

$$SUPPLY_{i,c,t} - PROCESS_{i,t} - \sum\nolimits_k FD_{z=\{i\},k,t} = \sum\nolimits_c PRIMARY_{i,c,t}$$

$$+ \sum\nolimits_k FD_{z=\{corn\},k,t} \;\; \forall t \quad Eq.(1.18)$$

The balance for corn production and corn-related products

$$SUPPLY_{i=\{corn\},c,t} = \sum\nolimits_c PRIMARY_{i=\{corn\},c,t} + \sum\nolimits_c CNE_{c,t} + PROCESS_{i=\{corn\},t}$$

$$+ \sum\nolimits_k FD_{z=\{corn\},k,t} \;\; \forall t \quad Eq.(1.19)$$

SI 1.2.3 Bioproduct constraints

$Eq.(1.20)$ shows the oil-related products balance, where corn can produce DDG while being converted to corn ethanol for feeding livestock k in cell c in year t ($FD_{z=\{DDG\},k,c,t}$ in tons) and be converted to corn oil for producing biodiesel ($QDSL_{j=\{DDG\},t}$ in gallons); soybeans can be converted to soybean oil. The left-hand side of the $Eq.(1.20)$ presents the usage of secondary product produced from the source of processed product j, and the right-hand side of the $Eq.(1.20)$ presents the production amount of processed product j.

$$\left[\sum\nolimits_k FD_{z=\{DDG\},k,t} + \frac{QDSL_{j,t}}{ddg2dsl}\right] \cdot 1[j = \{DDG\}] + \frac{QDSL_{j,t}}{oil2dsl_{i,j}} \cdot 1[j = \{corn\ oil, soybean\ oil\}] =$$

$$\sum\nolimits_c eth2ddg \cdot CNE_{c,t} \cdot 1[j = \{DDG\}] + raw2pro_{i,j} \cdot PROCESS_{i,t}$$

$$\cdot 1[j = \{corn\ oil, soybean\ oil\}] \;\; \forall t$$

$$Eq.(1.20)$$

The balance between corn used for producing corn oil:

$$QOIL_{j,t} = raw2pro_{i=\{corn\},j} \cdot PROCESS_{i=\{corn,cornCC\},t} \qquad \forall j = \{corn\ oil\}, t \quad Eq.(1.21)$$

The balance between DDG used for feedstock:

$$\sum\nolimits_{k} FD_{z=\{DDG\},k,t} + QDSL_{j=\{DDG\},t} \leq corn2eth \cdot \sum\nolimits_{c} CNE_{c,t} \qquad \forall t \quad Eq.(1.22)$$

The balance between biomass produced from corn stover and corn stover acreage:

$$BMASSCS_{d,c,t} = \sum\nolimits_{j=\{Stover\},r,n,v} csy_{r,n,v,c,t} \cdot CSPLANT_{r,n,v,d,c,t} \quad \forall d, c, t \quad Eq.(1.23)$$

The balance of the total biomass production from perennial crops p and corn stover in cell c in year t:

$$BMASS_{c,t} = \sum\nolimits_{p,a,d} py_{p,c} PAC_{p,a,d,c,t} + \sum\nolimits_{d} BMASSCS_{d,c,t} \quad \forall c, t \quad Eq.(1.24)$$

The quantity of corn ethanol produced (QCE_t) in year t is equal to the amount of corn used for producing corn ethanol in cell c in year t ($CNE_{c,t}$) multiplied by the conversion rate of producing corn ethanol from corn biomass ($corn\_to\_eth$).

$$QCE_t = corn2eth \cdot \sum\nolimits_{c} CNE_{c,t} \quad \forall t \quad Eq.(1.25)$$

SI 1.2.4 Livestock products constraints

The relation between animal units and the grazing land availability:

$$LS_{k=\{cattle\},t} \cdot as_{m,k} \leq \sum\nolimits_{g} \frac{al_{d=\{grassland\},c}}{\lambda_{g,c}} \quad \forall c, t \quad Eq.(1.26)$$

The balance of nutrition required by producing each livestock product:

$$NUTR_{u,k,t} = \sum\nolimits_{m} as_{m,k} \cdot nr_{an,u} \cdot LS_{k,t} \quad \forall u, k, t \quad Eq.(1.27)$$

The balance of calories required by producing each livestock product:

$$\sum_{u=\{calories\}} NUTR_{u,k,t} = \sum_{z} FD_{z=\{i,j\},k,t} \cdot fwc_{z=\{\boldsymbol{i},\boldsymbol{j}\}} \cdot re_{z,u=\{calories\}} \quad \forall k,t \quad Eq. (1.28)$$

The balance of protein required by producing each livestock product:

$$\sum_{u=\{protein\}} NUTR_{u,k,t} = \sum_{z} FD_{z=\{i,j\},k,t} \cdot fwc_{z=\{\boldsymbol{i},\boldsymbol{j}\}} \cdot re_{z,u=\{protein\}} \quad \forall k,t \quad Eq. (1.29)$$

The weight limit constraint of DDG used for producing each livestock product:

$$FD_{z=\{ddg\},k,t} \cdot fwc_{z=\{ddg\}} \leq \sum_{k} FD_{z=\{ddg\},k,t} \cdot fwc_{z=\{ddg\}} \cdot ddgwl_{k} \quad \forall k,t \quad Eq. (1.30)$$

The balance between soybeans used for producing soybeans meal as feedstock:

$$\sum_{k} FD_{z=\{soybeanmeal\},k,t} =$$

$$raw2pro_{i=\{soybeans\},j=\{soybeanmeal\}} \cdot PROCESS_{i=\{soybeans,soybeansCC\},t} \quad \forall t \quad Eq. (1.31)$$

SI 1.2.5 Policy constraints

The corn ethanol mandate constraint presents as

$$QCE_t \geq \delta_t \quad \forall t \quad Eq. (1.32)$$

where δ_t is the existing corn ethanol mandate target in year t.

The total amount of N leaching in cell c in year t ($NLEACH_{c,t}$) can be expressed as:

$$\sum_{i,d} rnlr_{r,n,v,c,t} RAC_{i,d,c,t} + \sum_{p,a,d} pnlr_{p,c,t} PAC_{p,a,d,c,t} = NLEACH_{c,t} \quad \forall c,t \quad Eq. (1.33)$$

where $nlr_{q,c,t}$ and $nlr_{p,c,t}$ are N leaching rate for row crops and perennial crops, respectively.

$$\sum_{c} de_{c,t}\, NLEACH_{c,t} \leq nl_t \quad \forall t \quad Eq. (1.34)$$

The N leaching limit in year t (nl_t) is an upper bound for the total amount of N leaching after considering the delivery efficiency in cell c in year t ($de_{c,t}$). However, the above constraint equation is deterministic, assuming the constraint can be met at a probability of 100%. This assumption may not be very realistic given the fact that there are several factors in nature influencing N leaching. Thus, a more realistic way to modify the assumption is to convert the deterministic constraint to a stochastic one using the chance-constraint method (Cardwell & Ellis, 1993; Ellis, 1987; Fujiwara et al., 1986; Sethi et al., 2006; Wang et al., 2015; Y. Zhou et al., 2018). The chance-constraint formula for N leaching constraint is:

$$Pr\left[\sum_{c} de_{c,t}\, NLEACH_{c,t} \leq nl_t\right] \geq \alpha \quad \forall t \qquad Eq. (1.35)$$

which ensures the likelihood of meeting the required N leaching limit in year t is realized at a minimum probability α. The stochastic version the N leaching constraint can be expressed as:

$$\sum_{c} \mu_c\, NLEACH_{c,t} + \Phi^{-1}(\alpha) \cdot \sqrt{\sum_{c} \left(\sigma_c NLEACH_{c,t}\right)^2} \leq nl_t \quad \forall t \qquad Eq. (1.36)$$

where μ_c is the average of N leaching delivery efficiency in cell c. $\Phi^{-1}(\alpha)$ is the inverse cumulative distribution function of a standard normal random variable. σ_c is standard deviation of N leaching delivery efficiency in cell c. A detailed derivation of chance-constraint can refer to Jacobs et al. (1997).

Table S3. Cover crop parameter assumptions.

Parameters	**Values**	**References**
N reduction	48% w/ winter rye	(Kaspar et al., 2012)
Yield change	Year 1: -5% Years 2 –5: unchanged Years 6 –10: +5%	(Majeed, 2023)
Cover crop fertilizer reduction (corn)	15 lbs of N/acre	(Majeed, 2023; Schnitkey et al., 2021)
Cover crop planting cost	$37/acre	(Zulauf & Schnitkey, 2022)
Cover crop cost saving from erosion/weed reduction	$9.5/acre	(Majeed, 2023; Myers et al., 2019)
Observed cover crop production in 2016	Grid level data for the model validation	(Zhou et al., 2022)

SI 2. Land Classification Description

This section describes the land classification used in this study. In Jiang et al. (2021), the raw Cropland Data Layer (CDL) was first aggregated into seven types in each year of 2008-2015: cropland, idle cropland, grassland, forest, shrubland, bare land, and built-up area. Then, they integrated the time series data and identified six land use types without land use change (LUC), permanent cropland, permanent grassland, permanent forest, permanent shrubland, permanent bare areas, and built-up areas, and three types of land use change (LUC), which are cropland in transition with confidence, cropland in transition with uncertainty, and other LUC areas (each definition is provided in the definition section).

To identify cropland in transition with confidence and uncertainty, they applied a logistic regression and a trend analysis to classify if pixels were cropland in transition with confidence or uncertainty. After classifying cropland in transition with confidence and uncertainty, they used land productivity as an indicator of land productivity and land vulnerability, which is determined by the sum of water erodibility and wind erodibility and as an indicator of land environmental conditions, to identify economically marginal land. Specifically, they calculated mean and standard deviation values of land productivity and land vulnerability as the threshold to distinguish between cropland in transition with the uncertainty and potential classification errors, which can be further classified into six subcategories (i.e., high/average/low productivity and high/low vulnerability), as shown in Figure S2.

Jiang et al. (2021)'s classification for marginal land with uncertainty (i.e., the blue area in Figure S2) is a relatively narrow classification, because they only classified land with "average productivity and low vulnerability" as marginal land with uncertainty. This study expands Jiang et al. (2021)'s classification for marginal land with uncertainty by also considering land with "high productivity" and "average productivity and high vulnerability" (i.e., the red area in Figure S2).

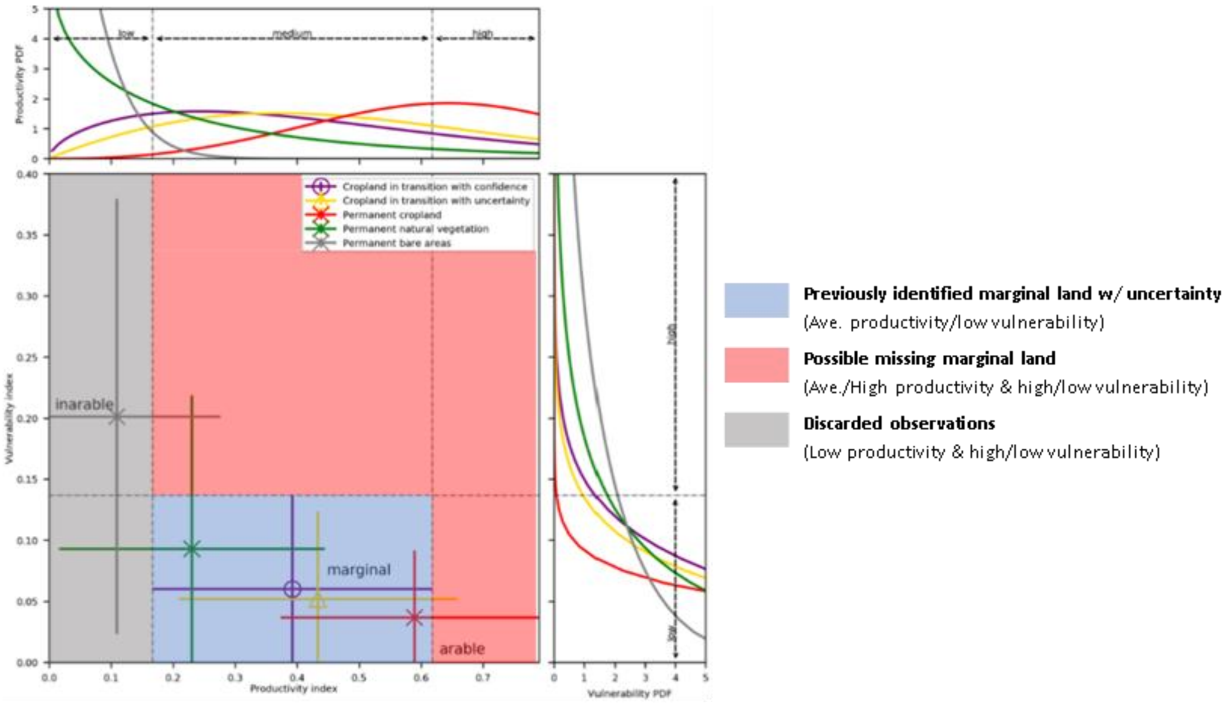

Figure S2. Land productivity and land vulnerability for different land use types.
Source: Modified from Jiang et al. (2021)

SI 3. Mathematical programming model validation results

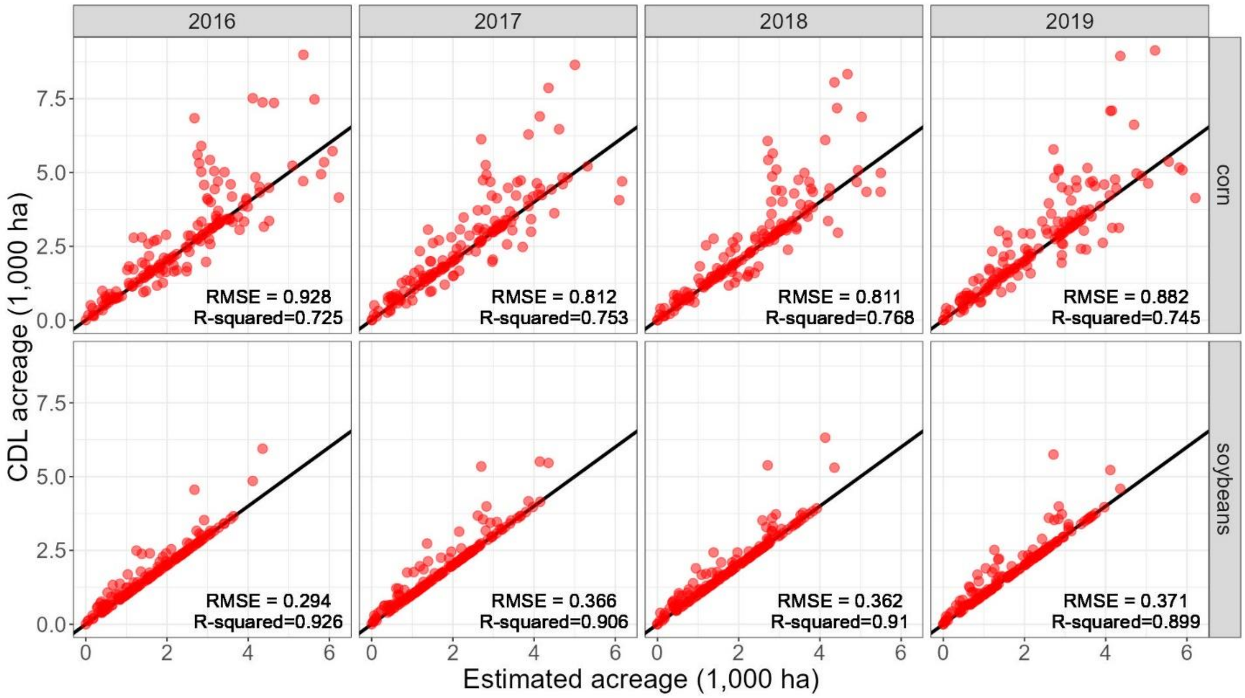

Figure S3. 10 km scale grid-by-grid validation for the major crops during 2016-2019.

Table S4. Validation results at the entire watershed level (Unit: ha)

Year	Scale	Corn			Soybeans			Alfalfa			Oats		
		Obs.	**Est.**	**Diff. (%)**	**Obs.**	**Est.**	**Diff. (%)**	**Obs.**	**Est.**	**Diff. (%)**	**Obs.**	**Est.**	**Diff. (%)**
2016	10 km	441,068	392,454	-11.02	286,341	267,553	-6.56	8,932	8,716	-2.42	819	799	-2.42
2017	10 km	419,726	372,852	-11.17	310,253	287,486	-7.34	6,050	5,953	-1.6	1,178	1,170	-0.69
2018	10 km	410,914	362,422	-11.8	318,413	295,129	-7.31	6,485	6,479	-0.08	1,175	1,171	-0.34
2019	10 km	429,695	379,611	-11.66	305,188	282,193	-7.53	6,228	6,063	-2.64	981	944	-3.76
2016	County	441,068	402,196	-8.81	286,341	274,432	-4.16	8,932	8,918	-0.16	819	819	0
2017	County	419,726	370,764	-11.67	310,253	296,071	-4.57	6,050	5,742	-5.08	1,178	1,178	0
2018	County	410,914	368,240	-10.39	318,413	300,840	-5.52	6,485	6,485	0	1,175	1,172	-0.28
2019	County	429,695	389,917	-9.26	305,188	289,854	-5.02	6,228	6,228	0	981	969	-1.16

Table S5. Validation results of cover crop adoption acreage at the entire watershed level (Unit: ha)

Year	Scale	Crop	Obs.	Est.	Diff. (%)
2016	10 km	Corn with the cover crop practice	16,100	16,923	5.1
2016	County	Corn with the cover crop practice	16,100	17,349	7.8

Note: Observed cover crop acreage data is from Zhou et al. (2022).

SI 4. County-scale model result

a. Land use change by crop types

b. Land use change by rotation types

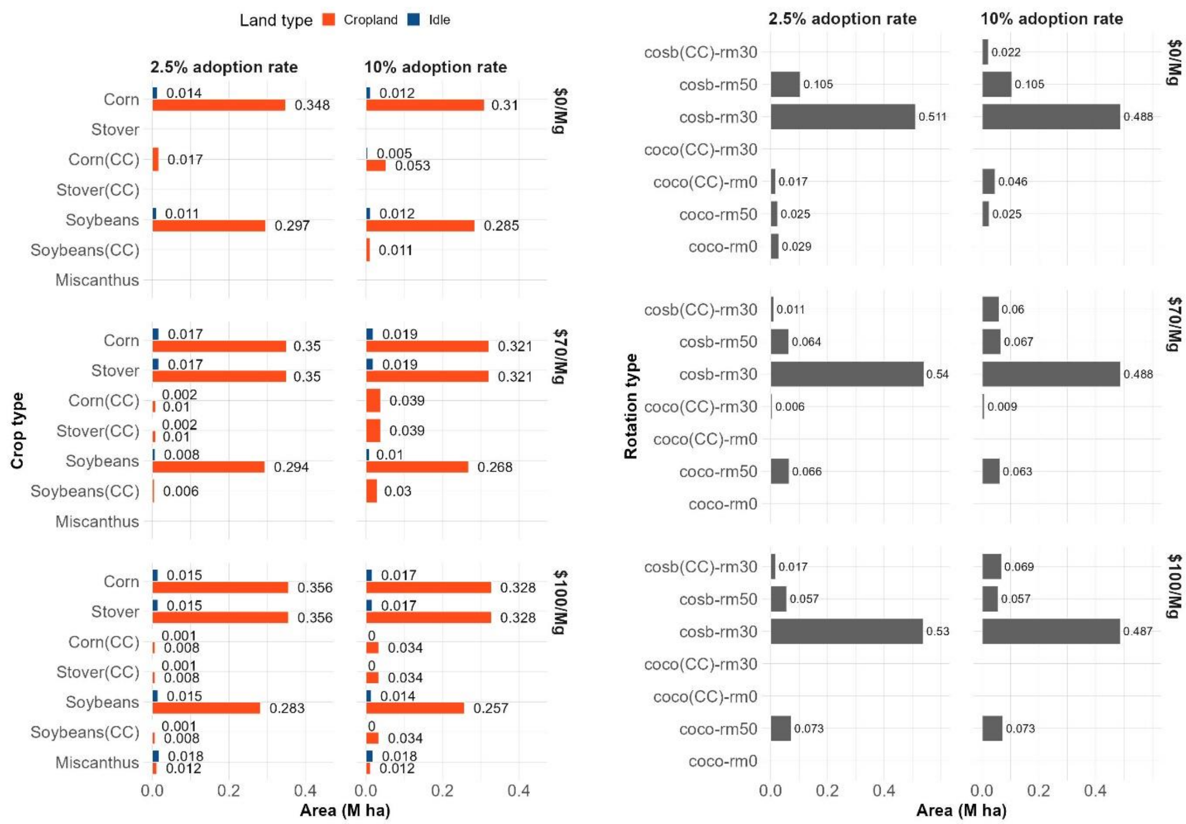

Figure S4. Effect of perennial and cover crop adoption on land use changes in 2045

Note: 'coco' denotes continuous corn rotation; 'cosb' denotes corn-soybean rotation; '(CC)' denotes a rotation with the cover crop practice; 'rm' denotes the corn stover removal rate.

a. Aggregated profit and subsidy

b. N leaching

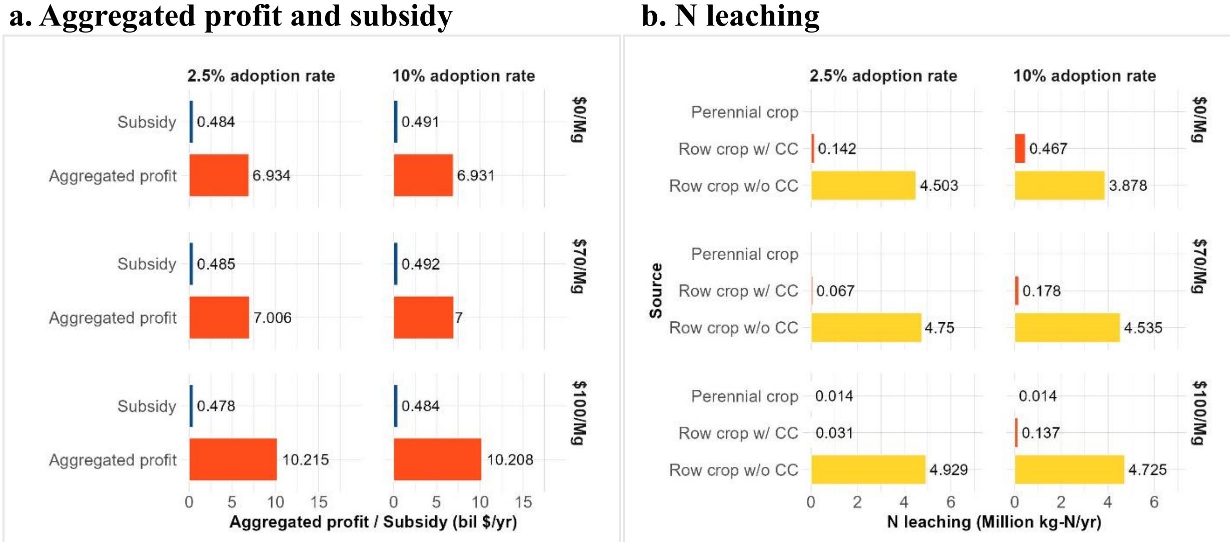

Figure S5. Effect of perennial and cover crop adoption on nutrient loss and aggregated profit in 2045

a. 2.5% cover crop adoption rate **b. 10% cover crop adoption rate**

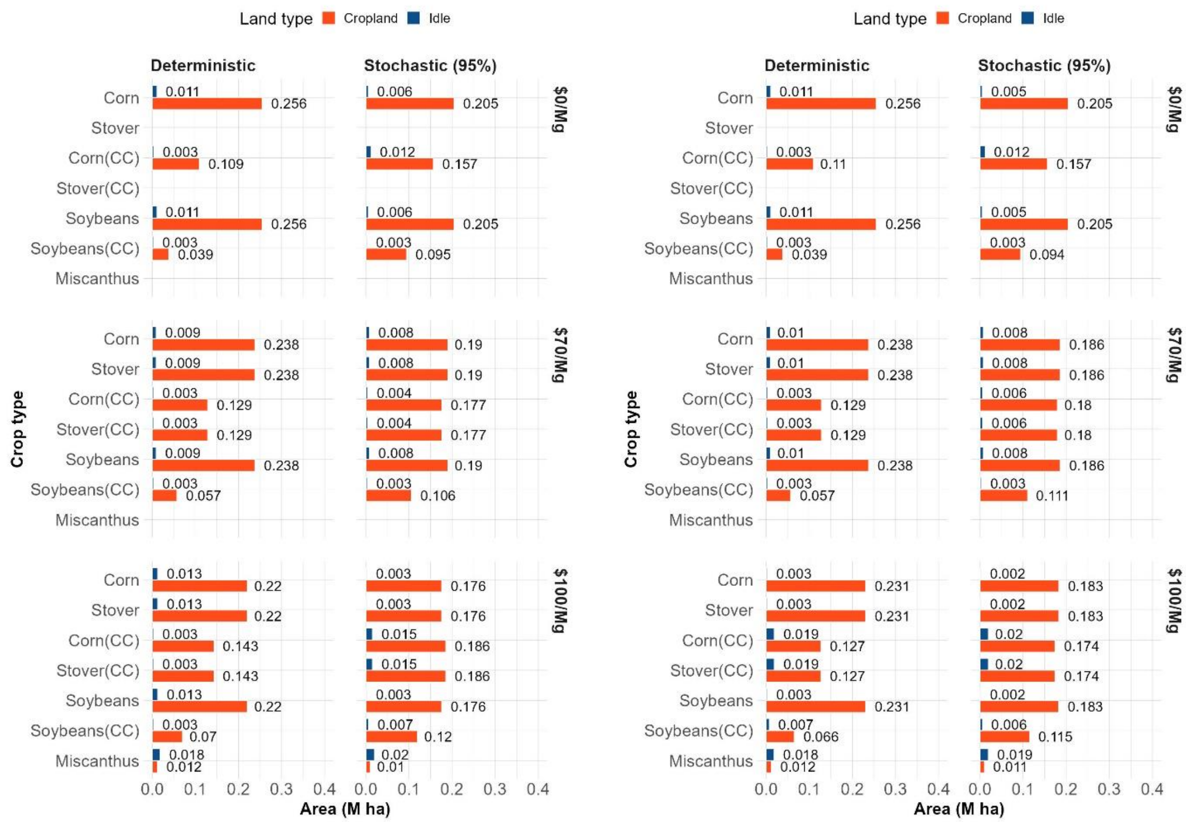

Figure S6. Effect of N reduction policy on land use changes in 2045

a. Aggregated profit and subsidy **b. N leaching**

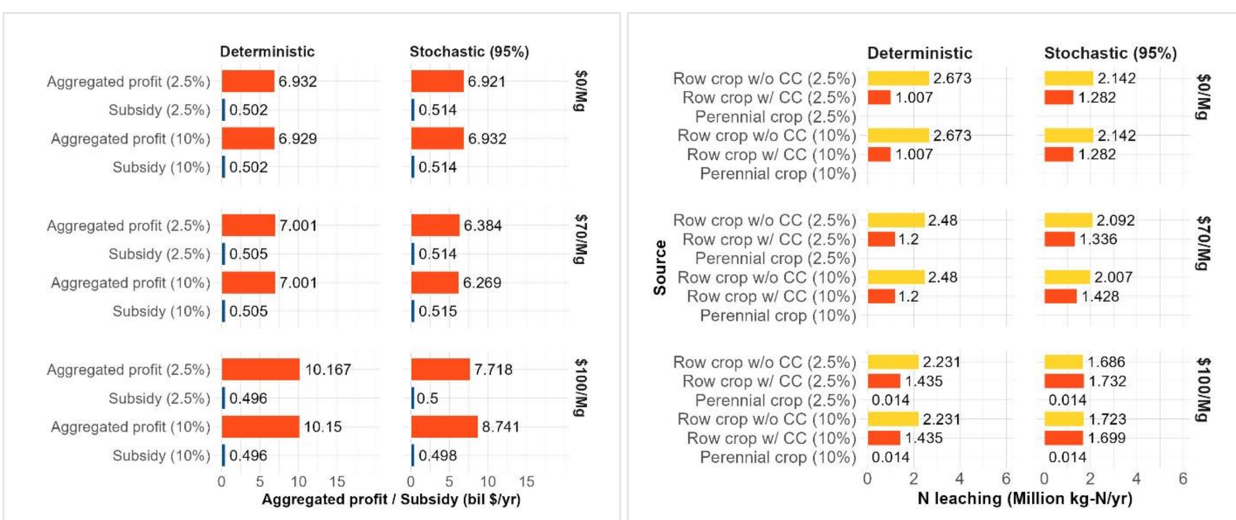

Figure S7. Effect of N reduction policy on nutrient loss and aggregated profit in 2045

Table S6. Estimated cover crop adoption rates under various scenarios in 2045

Required minimum cover crop adoption rate	N policy constraint	\$0/Mg	\$70/Mg	\$100/Mg
≥ 2.5%	No N constraint	2.50	2.50	2.50
	Deterministic	22.42	27.95	31.97
	Stochastic (95%)	38.78	42.16	47.84
≥ 10%	No N constraint	10.00	10.00	10.00
	Deterministic	22.42	27.95	31.97
	Stochastic (95%)	38.78	43.63	45.89

Unit: % of the total corn and soybean land

Table S7. N abatement cost (Nitrate tax) in 2045

Required minimum cover crop adoption rate	N policy constraint	\$0/Mg	\$70/Mg	\$100/Mg
≥ 2.5%	Deterministic	1.685	2.266	3.033
	Stochastic (95%)	2.169	2.283	2.933
≥ 10%	Deterministic	1.685	2.266	3.033
	Stochastic (95%)	2.169	2.274	2.838

Unit: \$/kg- N

SI 5. Corn yield distribution comparison between 10 km- and county-scales

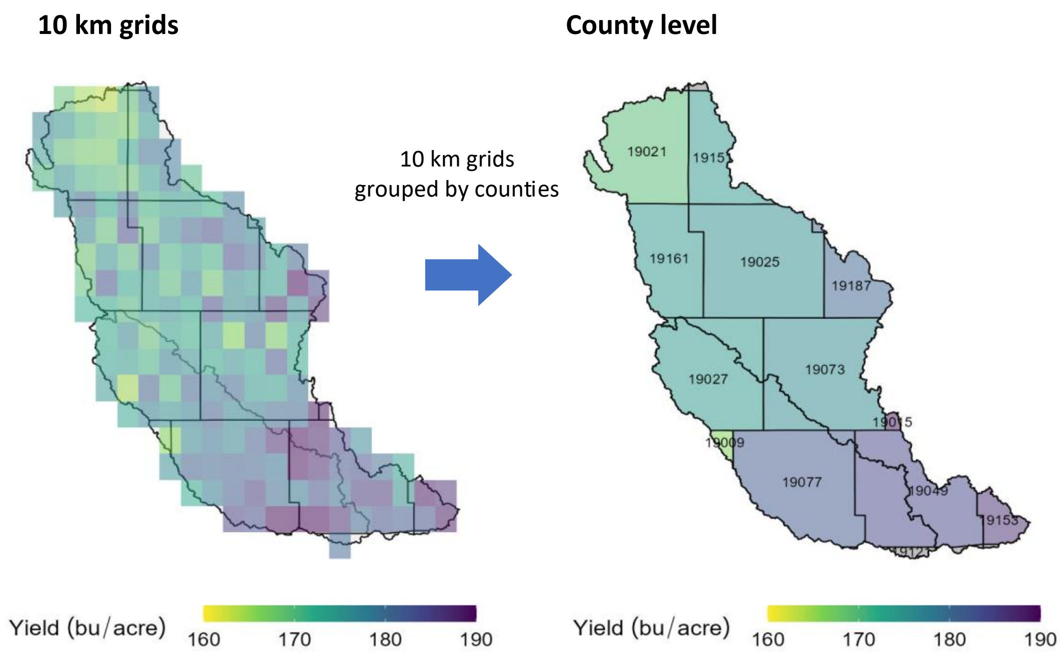

Figure S8. Illustration of converting continuous corn yield from 10 km-scale to county-scale.

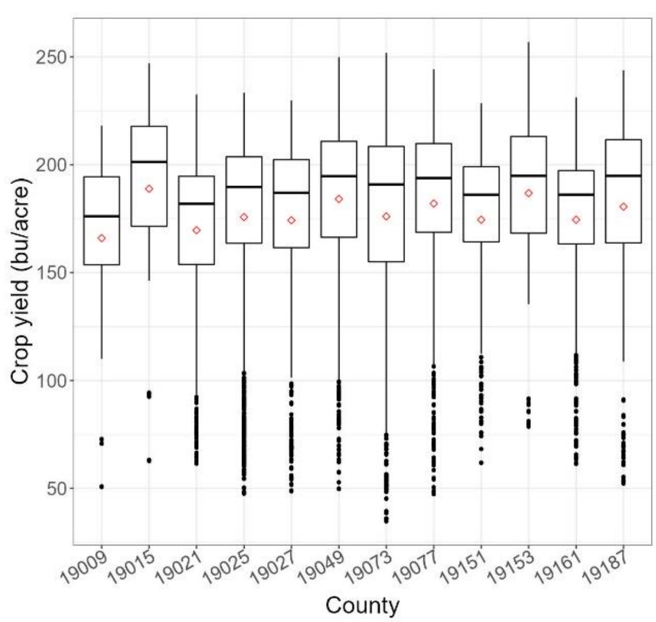

Figure S9. Distribution of continuous corn yield from all 10 km-scale grids in each county.

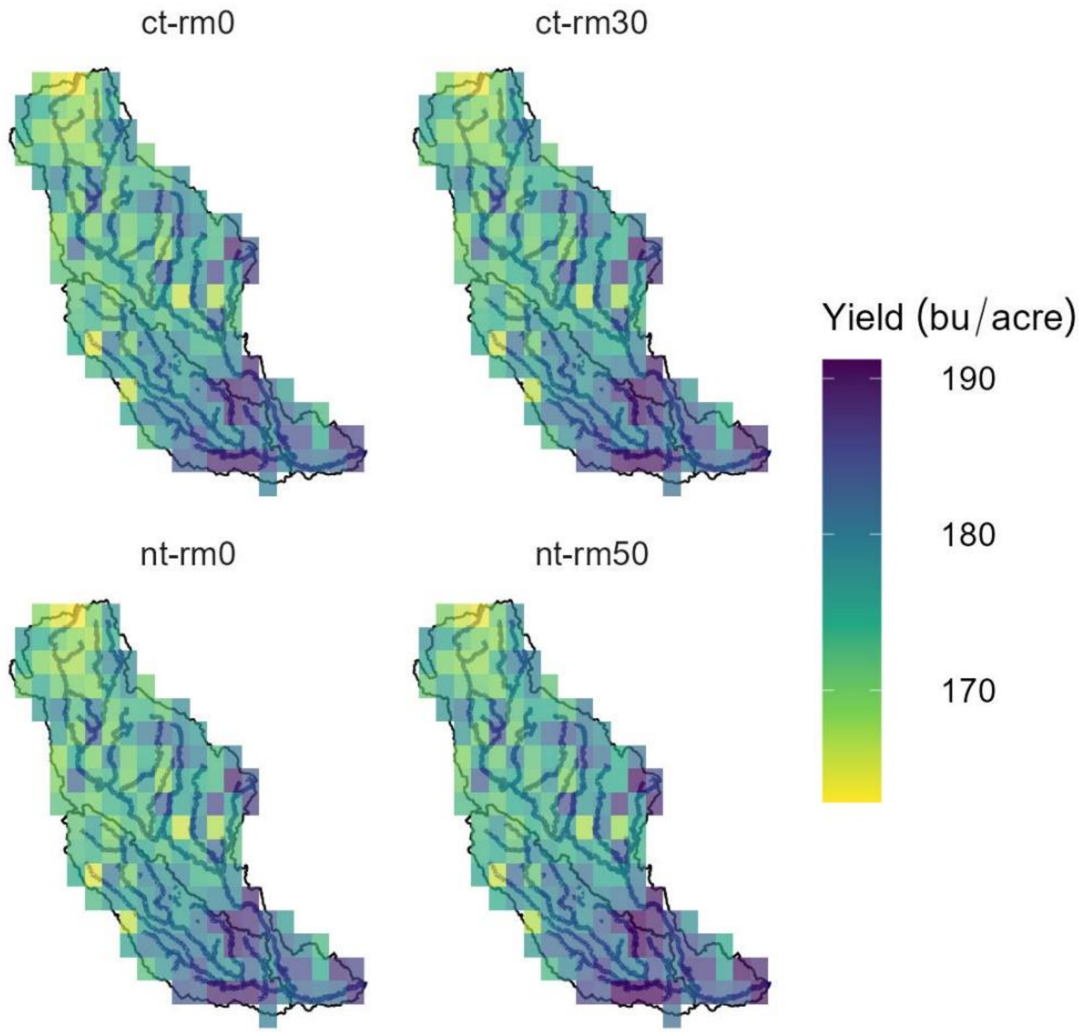

Figure S10. Spatial distribution of 35-year average continuous corn yield at 10 km-scale.

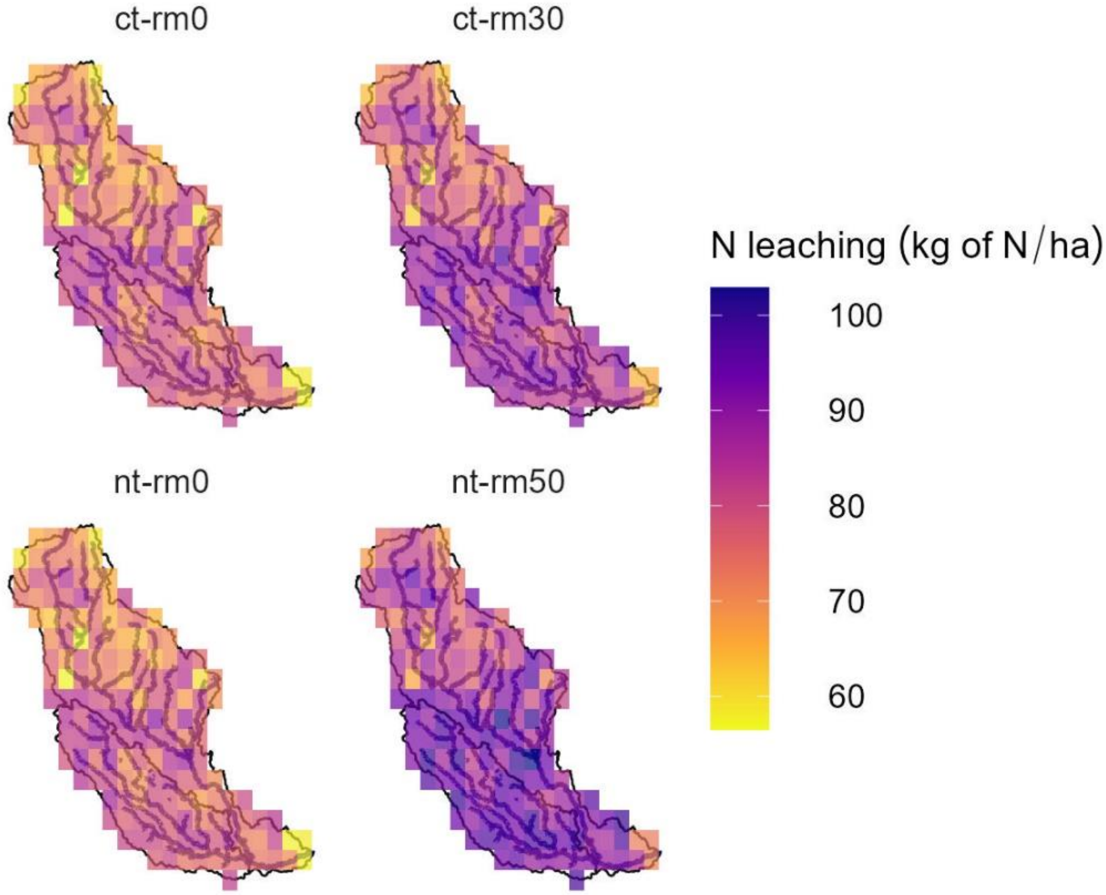

Figure S11. Spatial distribution of 35-year average N leaching from continuous corn land at 10 km-scale.

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