CARD Agricultural Policy Review
IOWA STATE UNIVERSITY OF SCIENCE AND TECHNOLOGY
Ames, Iowa • Fall 2023

Federal Food Policy Changes following the COVID-19 Pandemic

Katherine Harris-Lagoudakis and Beomyun Kim
kaharris@iastate.edu; beomyun@iastate.edu

THIS ARTICLE discusses changes in federal food policy following the aftermath of the COVID-19 pandemic. Many of the policy options that were created in response to high rates of unemployment and school closures have now sunset. This article discusses the implementation and phase-out of food policy options that were designed to assist households during the pandemic.

Changes to the Supplemental Nutrition Assistance Program (SNAP)

SNAP participation sharply increased with the onset of the COVID-19 pandemic. Figure 1 illustrates the number of households participating in SNAP (in millions) from January 2019 through June 2023. By May 2020, household-level SNAP participation had increased by 16% relative to January 2020. Surprisingly, the number of SNAP households has remained fairly steady, around 22 million, throughout the first half of 2023.

The amount of SNAP benefits each household was awarded also increased in response to the pandemic. A major component of this increase was the introduction of Emergency Allotments (EA benefits) as a policy option within the SNAP program. EA benefits removed the income deduction from the SNAP benefit formula, essentially paying all households the maximum benefit amount given their household size. All states adopted this policy option by April 2020. Figure 2 plots the mean SNAP benefit amount per person over time. Consistent with the time states adopted the policy option, there was a 32% increase in the mean benefit amount between March and April 2020.

Several additional adjustments to SNAP benefit amounts occurred throughout the COVID-19 pandemic. For example, the Consolidated Appropriations Act of 2021 authorized a 15% increase in SNAP benefits beginning in January 2021 and lasting through June 2021 (White House 2021). The American Rescue Plan Act in February 2021 later extended this increase through September 2021 (USDA 2021a). In October 2021, the US Department of Agriculture (USDA) announced that

In this issue:

it had updated the Thrifty Food Plan (TFP), which it uses to set the amount of food assistance people participating in SNAP receive, to reflect the cost of a healthy diet more accurately (USDA 2021b). The update to the TFP increased the maximum amount of SNAP benefits by 22%, effective in October 2021.

Importantly, EA benefits were only available as a policy option to states so long as the state had an active emergency or disaster declaration in place. As states phased out of having these declarations in place, EA benefits also began to be phased out of the SNAP program. Furthermore, in December of 2022, Congress passed legislation that sunset EA benefits in all states in March 2023 (USDA 2023c).

Figure 3 illustrates the four groups' average SNAP benefit per participant over time. These groups are categorized based on Emergency Allotment (EA) cessation timing, including the first half of 2021, the second half of 2021, 2022, and January to February 2023 (USDA 2023c). The y-axis represents the average SNAP benefit per participant, indicating the mean amount of assistance provided. The x-axis represents the monthly time intervals. The graph demonstrates a noticeable pattern where the average SNAP disbursement per participant decreases in the order of EA cessation. As each group exits the Emergency Allotment program at different time points, there is a corresponding decrease in the average SNAP disbursement per participant.

Since the sunset of EA benefits as a policy option in February of 2023, the SNAP program has largely returned to its pre-pandemic structure with some exceptions. Notably, the ability to utilize SNAP as a form of payment when shopping for groceries online was expanded during COVID-19 and appears now to be a permanent feature of the SNAP program. This is great news, not only for SNAP participants but also for online grocery retailers.

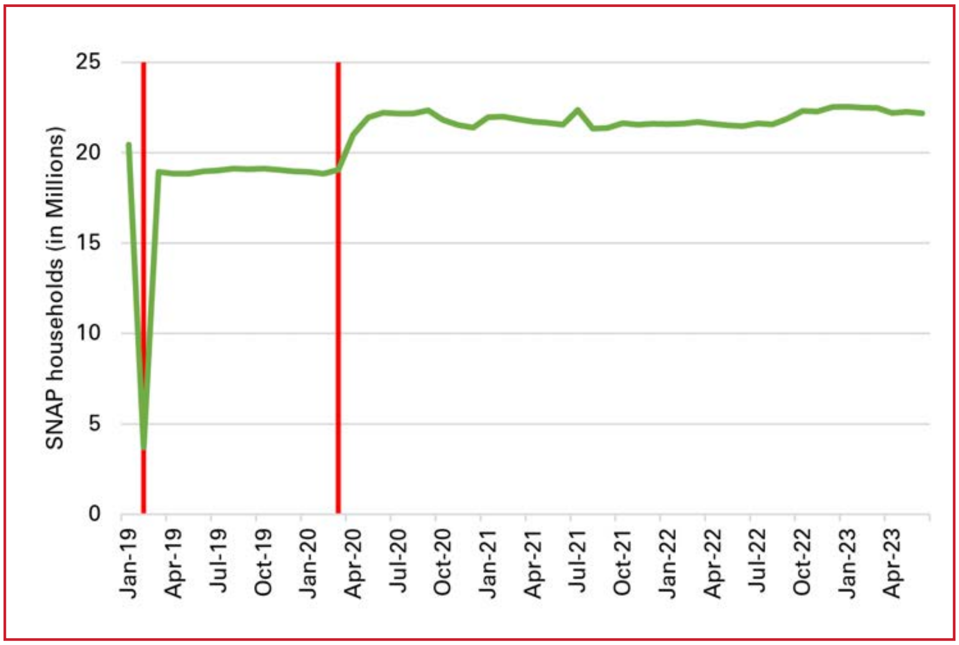

Figure 1. SNAP participating households.

Note: The first vertical bar represents the 2018–2019 federal government shutdown. The second vertical bar represents the onset of the COVID-19 pandemic.

Source: SNAP Data Tables (USDA 2023b).

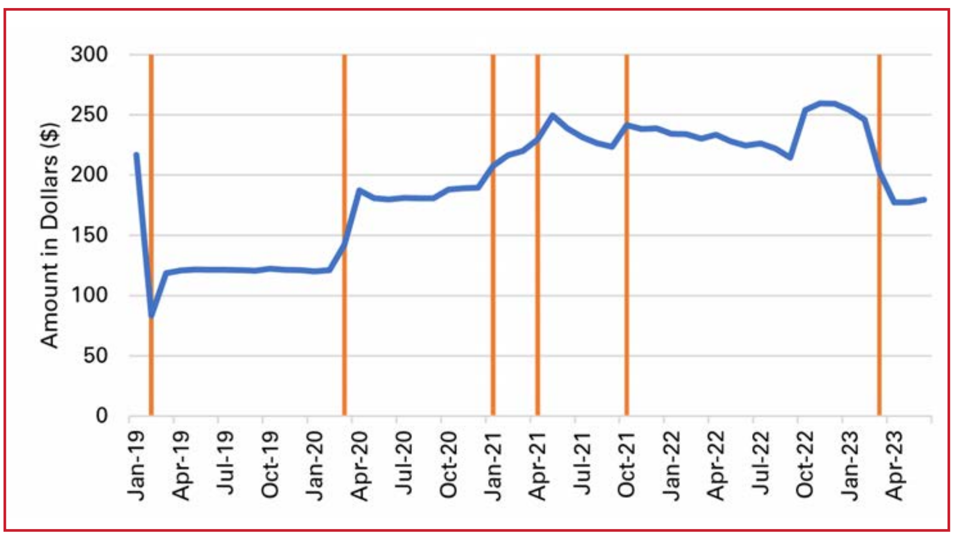

Figure 2. Average SNAP benefit amount per person.

Note: The first vertical bar represents the 2018–2019 federal government shutdown. The second bar represents the early days of the COVID-19 pandemic. The third bar represents the 15% benefit increase by the Consolidated Appropriations Act of 2021. The fourth bar represents an additional $95 increase for households not getting the EA because they were already getting the maximum benefits before COVID-19. The fifth bar represents the TFP re-evaluation, which increased the benefit amount by approximately 22%. The sixth bar represents the sunset of EA for the majority of states.

Source: SNAP Data Tables (USDA 2023b).

National School Lunch and the School Breakfast Program

In response to school closures and virtual learning formats, considerable changes were also made to the National School Lunch Program (NSLP) and the School Breakfast Program (SBP). The largest change was the introduction

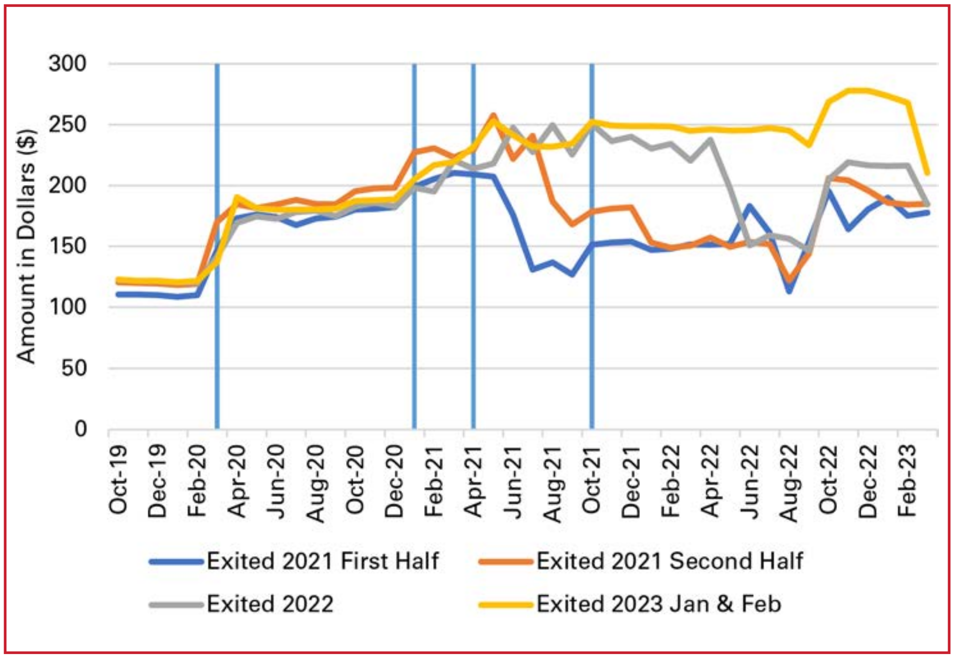

Figure 3. Average SNAP benefit per participant by EA exit timing.

Note: We divide our sample of 50 states and Washington, DC, into four groups based on the timing of EA exit. We calculate each group's weighted average of monthly per capita SNAP disbursement. We define population as SNAP participants at the state level. States sunset the EA-benefits policy in the following order: (1) Exited in 2021 first half: Idaho, North Dakota, Arkansas; (2) Exited in 2021 second half: Montana, Florida, Nebraska, South Dakota, Missouri, Tennessee, Mississippi; (3) Exited in 2022: Iowa, Wyoming, Kentucky, Alaska, Georgia, Indiana; (4) Exited in 2023 January: South Carolina; and, (5) Exited in 2023 February: All other states, and Washington, DC.

Source: SNAP Data Tables (USDA 2023b).

Figure 4. Predicted average P-EBT benefits for eligible students in the 2020–2021 school year.

Note: Figure 4 illustrates differences in the estimated P-EBT benefits allocated across different geographical areas.

Source: Authors' own calculation based on COVID-19 School Data Hub. 2023. District-Monthly Percentage In-Person, Hybrid, or Virtual.

of the Pandemic Electronic Benefits Transfer (P-EBT). P-EBT is a temporary program that provides additional food assistance to families with children eligible for free or reduced-price school meals but cannot receive them due to school closures or reduced hours during the COVID-19 pandemic. The Families First Coronavirus Response Act authorized the P-EBT program in March 2020. Since then, P-EBT has been extended and expanded several times. USDA administered the program in collaboration with state agencies and was funded by the federal government.

The P-EBT program provides a one-time benefit to eligible families to cover the cost of meals that children would have received if schools were open. The benefit amount varies by state and is calculated based on the number of days schools were closed due to the pandemic. The benefit is delivered to eligible families through an EBT card, which can be used to purchase food at authorized retailers. The eligibility for P-EBT is determined by the child's eligibility for free or reduced-price school meals based on income and household size. Children who attend schools participating in the Community Eligibility Provision (CEP) are also eligible for P-EBT.

Due to varying school learning formats, there is considerable variation across school districts in the amount of P-EBT that school-aged children are eligible for. In school year 2020 to 2021 (SY 2020/2021), for example, some schools offered fully remote learning while others implemented a hybrid model with a mix of in-person and remote instruction.

Figure 4 illustrates differences in the estimated P-EBT benefits allocated across different geographical areas.[1] Each region is color-coded to indicate the level of P-EBT disbursement, with darker

1. To estimate the amount of P-EBT for which students are eligible, we use data from the COVID-19 School Data Hub (COVID-19 School Data Hub 2023). Based on the learning model ratio for each school district, we predict school opening days for each school district for each month. Then, we sum up these expected school opening days to get the predicted total school opening days in SY 20–21. Finally, we multiply by $6.84 (NSLP reimbursement rates in SY20–21) to get the anticipated P-EBT benefits for eligible students.

shades representing higher amounts and lighter shades representing lower amounts. This figure demonstrates the pronounced differences in estimated P-EBT disbursement amounts across different regions of the United States.

Summary and conclusions

This article summarizes the implementation and sunset of the temporary policy options within SNAP, NSLP, and the SBP in response to the COVID-19 pandemic. Within the SNAP program, COVID-19 policy options greatly expanded benefit amounts and the ability to utilize SNAP benefits as forms of payment when purchasing grocery products online. While the temporary benefit increases have sunset as policy options, the ability to utilize EBT as a form of payment online has remained. Like SNAP, the major changes to NSLP and SBP delivery have also sunset, largely due to schools returning to in-person learning. However, the advent of Summer Electronic Benefit Transfer (Summer EBT), a program that pays out EBT benefits during the summer months when school meals are not served, has emerged and is also positioned to become a permanent feature of the food and nutrition assistance landscape (USDA 2023).

References

COVID-19 School Data Hub. 2023. District-Monthly Percentage In-Person, Hybrid, or Virtual. Retrieved from https://www.covidschooldatahub.com/.

United States Department of Agriculture. 2021a. SNAP – Extension of Temporary Increase in Maximum Allotments due to COVID-19. Retrieved from https://www.fns.usda.gov/snap/Extension-of-Temporary-Increase-in-Maximum-Allotments.

United States Department of Agriculture. 2021b. Thrifty Food Plan, 2021. Retrieved from https://www.fns.usda.gov/cnpp/thrifty-food-plan-2021.

United States Department of Agriculture. 2023a. Guidance for State Implementation of Summer EBT in 2024. Retrieved from https://www.fns.usda.gov/sebt/state-implementation-of-summer-ebt-2024.

United States Department of Agriculture. 2023b. SNAP Data Tables. Retrieved from https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap.

United States Department of Agriculture. 2023c. SNAP Emergency Allotments are Ending. Retrieved from https://www.usda.gov/media/blog/2023/02/08/snap-emergency-allotments-are-ending.

White House. 2021. Fact Sheet: President Biden's New Executive Actions Deliver Economics Relief for American Families and Businesses Amid the COVID-19 Crises. Retrieved from https://www.whitehouse.gov/briefing-room/statements-releases/2021/01/22/fact-sheet-president-bidens-new-executive-actions-deliver-economic-relief-for-american-families-and-businesses-amid-the-covid-19-crises/.

Suggested citation

Harris-Lagoudakis, K., and B. Kim. 2023. "Federal Food Policy Changes following the COVID-19 Pandemic." Agricultural Policy Review Fall 2023. Center for Agricultural and Rural Development, Iowa State University. Available at: https://agpolicyreview.card.iastate.edu/fall-2023/federal-food-policy-changes-following-covid-19-pandemic.■

Strategic Risk and Collective Action in Agriculture

Ariel Singerman and Sergio H. Lence
singerman@ufl.edu; shlence@iastate.edu

COLLECTIVE ACTION is advocated as a solution to common challenges encountered by agricultural producers, including accessing new markets, sharing capital investment expenses, and negotiating with companies both upstream and downstream in the supply chain (Bouamra-Mechemache and Zago 2015). Collective action is also proposed as a solution to problems related to externalities and public goods within the agricultural community and between farmers and other economic actors (Ayer 1997). Recently, there is growing interest in utilizing collective agri-environmental strategies to efficiently deliver public goods, such as biodiversity, water availability and quality, resilience against fires and flooding, storage of carbon to reduce greenhouse gas emissions, and enhanced agricultural landscapes (Vanni 2014).

A major hindrance for the adoption of collective action, however, is its inherent nature of public goods, which are characterized by non-excludability and non-rivalry and create the potential for opportunistic behavior. The core issue at hand, which at the same time introduces risk, is that individual's rewards are contingent not only on their own actions but also on the actions of others. Strategic risk occurs when agents' beliefs regarding the actions of other individuals influence their choices. Contrastingly, non-strategic risk refers to situations where the actions of others do not affect agents' decisions.

As a case study, we examine voluntary pest control, which can be seen as a collective-action problem similar to contributing to the provision of a public good. The agricultural economics literature has not given enough attention to the effect of uncertainty on the overall effectiveness of collective action endeavors, as well as the opportunity costs associated with alternatives to collective action. In this regard, it is crucial to note that since the probabilities associated with strategic risk rely on individuals' beliefs about the decisions made by others, in principle it should be possible to design policy interventions aimed at influencing the beliefs of participants in collective action. By doing so, it would become feasible to impact the likelihood of success in collective action initiatives.

"When it comes to pest control, the objective of government regulation should be to encourage producers to adopt pest control practices that align more closely with the social optimum."

Employing collective action as an approach to control pests

Since the 1950s, the introduction of synthetic pesticides has provided farmers with a cost-effective and efficient means of pest control within their own farms, independent of the opinions and actions of their neighbors (Hendrichs et al. 2007). Consequently, individual chemical pest management has become the predominant approach in pest control. However, despite the extensive use of chemicals, an estimated 10%–35% of crop production in the United States still suffers losses due to pest damage (Pimentel et al. 1993).

One significant concern regarding the practice of individual chemical pest management is that the mobility of pests undermines the effectiveness of the approach (Hendrichs et al. 2005). Consequently, focusing solely on site-specific pest management neglects the collective aspect of the problem (Perrings et al. 2002).

Because of the recurrence of pest infestations from neighboring farms, the actions taken by farmers at the individual level have minimal impact on the pest density in future periods (Lazarus and Dixon 1984). As a result, from an economic standpoint, individual pest management creates an externality that leads to a divergence between private and social optimal outcomes (Regev, Gutierrez, and Feder 1976). In particular, individual management leads to less pest control than would be optimal when viewed from the perspective of society as a whole (Miranowski and Carlson 1986). Achieving effective control of mobile pests relies heavily on the actions of neighboring farmers. This characteristic highlights the problem as a collective-action dilemma, where there are tradeoffs between individual and collective interests. By adopting collective pest control approaches, such as area-wide pest management (AWPM) programs, to deal with the externalities associated with individual pest management, it may become feasible to achieve an outcome closer to the socially optimal one.

Usually, collective-action dilemmas are addressed through either top-down regulations or bottom-up approaches. When it comes to pest control, the objective of government regulation should be to encourage producers to adopt pest control practices that align more closely with the social optimum. In theory, an ideal policy approach would involve imposing taxes on the usage of pest control chemicals to account for its social costs (Waterfield and Zilberman 2012). Alternatively, a government regulation could establish a quota on the total amount of pest control treatment allowed, set at the socially optimal level, and enable farmers to trade their treatment rights amongst themselves. However, taxes and quotas are often impractical for addressing pesticide externalities due to the diverse environmental and human health effects of pesticides, which may vary across farms and regions. In addition, the environmental costs associated with pesticide pollution are influenced by the spatial and temporal aspects of pesticide applications. Furthermore, the non-point source nature of pesticide pollution poses a challenge for implementing efficient policies, as monitoring expenses are often high and identifying the precise sources of pollution is rare (Sexton, Lei, and Zilberman 2007). Consequently, the difficulties involved in devising market-based policies make command-and-control approaches, where the government determines the permissibility and conditions of specific treatments (Zilberman and Millock 1997), an attractive alternative.

All forms of chemical pest control contribute to the creation of pest resistance externalities, because the stock of treatment efficacy is a shared resource accessible to all farmers in a particular region (Regev, Gutierrez, and Feder 1976). This common availability of treatment leads to an externality, as the usage of treatment by one farmer affects other farmers without compensating them. In the absence of regulation, excessive utilization and subsequent development of resistance are outcomes to be expected. Due to the presence of numerous such potential externalities, it might be more advantageous to make pest management decisions at the regional level rather than the individual farm level. When growers collaborate on pest control efforts, they can internalize externalities and enhance the efficiency of pest control measures. As a result, a bottom-up approach may become appealing, particularly when considering the financial limitations of governments, the challenges associated with implementing top-down regulations, and the high costs and enforcement difficulties that typically arise with top-down regulations in agricultural contexts (Ayer 1997; Ervin and Frisvold 2016).

"The coordination frontier may serve as a valuable tool in mitigating the strategic uncertainty associated with voluntary coordination programs."

While a community-based approach to address collective-action challenges can be more effective and lead to reduced transaction costs compared to command-and-control or payment-based approaches (Ostrom 2010), the absence of suitable institutions or incentives to encourage farmer participation may hinder the adoption of cooperative solutions (Loehman and Dinar 1994). A major challenge for establishing institutional capacity is that it requires a significant amount of time (Ervin and Frisvold 2016). However, the risk of pest invasions depends on how humans respond to the threat (Perrings et al. 2002). As a result, the timeframe required to establish institutions and cultivate trust among stakeholders for a centralized collective-action response differs significantly from the urgent response needed to address the immediate danger presented by a plant pathogen.

In certain situations, there may be benefits in initially adopting a faster yet temporary decentralized collective action strategy, such as a voluntary AWPM approach, as a means of bridging the gap until the establishment of appropriate community-based institutions. This approach is particularly relevant when the policy response is likely to be more gradual, such as the case of plant diseases vectored by pests (which may be dealt with less urgency than, e.g., animal diseases, because they are not transmitted to humans). However, voluntary coordination encounters challenges akin to those associated with contributing to the provision of a public good, most prominently stakeholder participation.

Participating in the provision of a public good, such as regional pest control by means of an AWPM program, carries inherent risks. The successful provision of the public good relies on achieving a critical mass of participants who cooperate. If this critical mass is not reached, the public good is not effectively provided, and those who contributed to it experience lower payoffs. Consequently, opting out becomes a safe strategy for an individual player, but it leads to reduced individual gains and a suboptimal social outcome. Hofstadter (1985) characterizes strategic uncertainty as “reverberant doubt,” which refers to the initial small doubts players have about the possibility of collectively attaining a more beneficial cooperative outcome. Over time, these doubts “reverberate,” ultimately eroding the individual player's initial commitment to the cooperative strategy and leading them to opt out instead.

The coordination frontier: A practical tool for AWPM

The coordination frontier developed by Lence and Singerman (2022) is a practical method for evaluating the likelihood of achieving success in a voluntary coordination program. The coordination frontier measures the impact of two key factors that contribute to the uncertainty involved in AWPM: (*a*) the extent to which a change in the coordination threshold affects the overall probability of successful coordination; and, (*b*) the extent to which the probability of successful coordination changes with increasing opportunity costs of coordination. By utilizing the coordination frontier, one can not only infer the circumstances necessary for different levels of voluntary coordination to be successful, but also determine the economic incentives required to facilitate its effectiveness.

The coordination frontier may serve as a valuable tool in mitigating the strategic uncertainty associated with voluntary coordination programs. By offering public information, it may help align beliefs among growers, ameliorate strategic uncertainty, and improve coordination.

The collaboration of farmers through collective action plays a vital role in tackling not just the external effects stemming from neighboring farmers’ choices regarding pest control, but also those associated with pesticide resistance. The United States alone suffers approximately USD $9 billion in annual losses due to pesticide resistance (Palumbi 2001), a problem further exacerbated by the growing global dependence on pesticides. Nevertheless, there have been no new herbicides with alternative modes of action introduced in the past three decades (Gould, Brown, and Kuzma 2018).

According to Ervin and Frisvold (2016), farmers perceive the management of resistance in mobile weeds to be dependent on the actions of their neighbors. This belief often discourages proactive resistance management. As highlighted by Dover and Croft (1986), pesticide resistance exacerbates the negative externalities associated with pesticide usage, because it leads to an increased reliance on pesticides to counteract the reduced susceptibility of pests. Furthermore, pesticide resistance can give rise to additional negative externalities.

The negative spatial externalities resulting from the absence of collective action in pest control are notably more severe and challenging to address in the context of perennial crops. However, the risks and decision-making patterns stemming from strategic interactions to combat pests and diseases that impact different crops, as well as the rising issue of pesticide resistance in weeds, remain essentially the same for perennial as for annual crops.

Policy implications

A fundamental feature of collective action is its characterization by strategic risk, which involves probabilities that rely on individuals' perceptions of the choices made by others. Consequently, policy interventions can potentially influence the prospects of success in collective-action endeavors by modifying the beliefs held by participants. One clear intervention approach involves enhancing farmers’ understanding of the economic advantages associated with collective action and providing them with information regarding the overall likelihood of success. An example of such intervention is the establishment of self-help groups, described by Desai and Joshi (2014) as organizations that aim to enhance social cohesion through a combination of educational efforts, access to financial resources, and connections to broader development programs.

Singerman and Useche (2019) reinforce the idea that providing public information regarding positive outcomes has the potential to increase anticipated rewards and reduce uncertainties concerning the behavior of others. Consequently, social learning, wherein individuals acquire knowledge from observing the decisions of others, becomes instrumental in effectively managing externalities. Importantly, the social learning process can occur through extension activities, as they play a pivotal role in fostering collective action and, thus, contribute to enhanced social welfare (Singerman and Useche 2019).

Upcoming research

In the near future, we plan on collecting data from farmers in Iowa and Argentina to gain a better understanding of the factors, including strategic risk, that affect their preferences regarding whether to adopt individual versus collective action to combat the increasing and problematic spread of herbicide-resistant weeds.

References

Ayer, H.W. 1997. “Grass Roots Collective Action: Agricultural Opportunities.” Journal of Agricultural and Resource Economics 22(1):1–11. https://www.jstor.org/stable/40986928.

Bouamra-Mechemache, Z., and A. Zago.

2015. “Introduction: Collective Action in Agriculture.” European Review of Agricultural Economics 42(5):707–711. https://doi.org/10.1093/erae/jbv027.

Dale, J., A. James, J. Paul, H. Khanna, M. Smith, S. Peraza-Echeverria, F. Garcia-Bastidas, G. Kema, P. Waterhouse, K. Mengersen, and R. Harding. 2017. “Transgenic Cavendish Bananas with Resistance to Fusarium Wilt Tropical Race 4.” Nature Communications 8:1496. https://doi.org/10.1038/s41467-017-01670-6.

Desai, R.M., and S. Joshi. 2014. “Collective Action and Community Development: Evidence from Self-Help Groups in Rural India.” The World Bank Economic Review 28(3):492–524. https://doi.org/10.1093/wber/lht024.

Dover, M.J., and B.A. Croft. 1986. “Pesticide Resistance and Public Policy.” BioScience 36(2):78–85. https://doi.org/10.2307/1310107.

Ervin, D.E., and G.B. Frisvold. 2016. “Community-Based Approaches to Herbicide-Resistant Weed Management: Lessons from Science and Practice.” Weed Science 64(1):609–626. https://doi.org/10.1614/WS-D-15-00122.1.

Gould, F., Z.S. Brown, and J. Kuzma. 2018. “Wicked Evolution: Can We Address the Sociobiological Dilemma of Pesticide Resistance?” Science 360:728–732. https://doi.org/10.1126/science.aar3780.

Hendrichs, J., J.B. Vreysen, W.R. Enkerlin, and J.P. Cayol. 2005. “Strategic Options in Using Sterile Insects for Area-Wide Integrated Pest Management.” In V.A. Dyck, J. Hendrichs, and A.S. Robinson (eds.) Sterile Insect Technique: Principles and Practice in Area-Wide Integrated Pest Management, 563–602. IAEA, Springer, Dordrecht: The Netherlands. https://doi.org/10.1007/1-4020-4051-2_22.

Hendrichs, J., P. Kenmore, A.S. Robinson, and M.J.B. Vreysen. 2007. “Area-Wide Integrated Pest Management (AW-IPM): Principles, Practice and Prospects.” In M.J.B. Vreysen, A.S. Robinson, and J. Hendrichs (eds.) Area-Wide Control of Insect Pests: From Research to Field Implementation, 3–31. Springer, AA Dordrecht: The Netherlands. https://doi.org/10.1007/978-1-4020-6059-5_1.

Hofstadter, D.R. 1985. Metamagical Themas: Questing for the Essence of Mind and Pattern. Basic Books: New York.

Lazarus, W.F., and B.L. Dixon. 1984. “Agricultural Pests as Common Property: Control of the Corn Rootworm.” American Journal of Agricultural Economics 66:456–465. https://doi.org/10.2307/1240924.

Lence, S.H., and A. Singerman. 2022. “When Does Voluntary Coordination Work? Evidence from Area-Wide Pest Management.” American Journal of Agricultural Economics 105(1):243–264. https://doi.org/10.1111/ajae.12308.

Loehman, E., and A. Dinar. 1994. “Cooperative Solution of Local Externality Problems: A Case of Mechanism Design Applied to Irrigation.” Journal of Environmental Economics and Management 26:235–256. https://doi.org/10.1006/jeem.1994.1015.

Miranowski, J.A., and G. Carlson. 1986. “Economic Issues in Public and Private Approaches to Preserving Pest Susceptibility.” In Committee on Strategies for the Management of Pesticide Resistance Pest Populations, Pesticide Resistance: Strategies and Tactics for Management. Washington, DC: National Academy Press. https://nap.nationalacademies.org/read/619/chapter/35.

Ostrom, E. 2010. “Analyzing Collective Action.” Agricultural Economics 41(1):155–166. https://doi.org/10.1111/j.1574-0862.2010.00497.x.

Palumbi, S.R. 2001. “Humans as the World’s Greatest Evolutionary Force.” Science 293:1786–1790. https://doi.org/10.1126/science.293.5536.1786.

Perrings, C., M. Williamson, E.B. Barbier, D. Delfino, S. Dalmazzone, J. Shogren, P. Simmons, and A. Watkinson. 2002. “Biological Invasion Risks and the Public Good: An Economic Perspective.” Conservation Ecology 6(1):1. http://www.consecol.org/vol6/iss1/art1/.

Pimentel, D., H. Acquay, M. Biltonen, P. Rice, M. Silva, J. Nelson, V. Lipner, S. Giordano, A. Horowitz, and M. D’Amore. 1993. “Assessment of Environmental and Economic Impacts of Pesticide Use.” In D. Pimentel, and H. Lehman (eds.) The Pesticide Question: Environment, Economics and Ethics, 47–84. Chapman & Hall: New York. https://doi.org/10.1007/978-0-585-36973-0_3.

Regev, U., A.P. Gutierrez, and G. Feder. 1976. “Pests as a Common Property Resource: A Case Study of Alfalfa Weevil Control.” American Journal of Agricultural Economics 58:186–197.

Sexton, S.E., Z. Lei, and D. Zilberman. 2007. “The Economics of Pesticides and Pest Control.” International Review of Environmental and Resource Economics 1:271–326. http://dx.doi.org/10.1561/101.00000007.

Singerman, A., and P. Useche. 2019. “The Role of Strategic Uncertainty in Area-Wide Pest Management Decision of Florida Citrus Growers.” American Journal of Agricultural Economics 101(4):991–1011. https://doi.org/10.1093/ajae/aaz006.

Vanni, F. 2014. Agriculture and Public Goods: The Role of Collective Action. Springer: New York. https://doi.org/10.1007/978-94-007-7457-5.

Waterfield, G., and D. Zilberman. 2012. “Pest Management in Food Systems: An Economic Perspective.” Annual Review of Environmental Resources 37:223–245. https://doi.org/10.1146/annurev-environ-040911-105628.

Zilberman, D., and K. Millock. 1997. “Pesticide Use and Regulation: Making Economic Sense Out of an Externality and Regulation Nightmare.” Journal of Agricultural and Resource Economics 22(2):321–332. https://www.jstor.org/stable/40986951.

Suggested citation

Singerman, A., and S. Lence. 2023. "Strategic Risk and Collective Action in Agriculture." Agricultural Policy Review Fall 2023. Center for Agricultural and Rural Development, Iowa State University. Available at: https://agpolicyreview.card.iastate.edu/fall-2023/strategic-risk-and-collective-action-agriculture.■

Agricultural Projections Going into 2024

Lee Schulz and Chad Hart
lschulz@iastate.edu; chart@iastate.edu

USDA'S WORLD Agricultural Supply and Demand Estimates (WASDE) report outlines the current view for agricultural markets over the next 12–18 months. In general, extreme weather events and domestic and international economic concerns have shaped the agricultural projections for the near future. While US meat demand remains resilient, cattle numbers have continued to decline due to drought and high production costs. Meanwhile, USDA projects the pork and poultry industries will grow. Livestock prices have a mixed outlook for 2024, with beef and pork prices expected to increase, while prices for broilers and turkeys fall. This year's acreage shifts seem to have bigger impacts on crop production than the ongoing drought, with corn acreage and production jumping higher, while soybean area and production fell. Crop usage eroded from sustained higher prices; however, the forecast shows a rebound in crop usage for the 2023 crops, with the exception of soybean exports.

For the livestock sector, the 2023 calendar year has been another challenging year. Drought continued to be a problem across a sizable chunk of the country, limiting pasture use and constraining herd size. Meat demand has been mixed. For beef, domestic consumption has been solid, but international consumption has retreated. Meanwhile, for pork, it is the opposite, as international consumption has increased, while domestic consumption is weaker. While prices are relatively strong (with the exception of pork), producers continue to face higher costs, limiting profitability. Table 1 shows the

Table 1. USDA Livestock Projections

	2023		2024		
	Forecast	**Change from September**	**Forecast**	**Change from September**	**Change from 2023 to 2024**
Production			(Billion Pounds)		
Beef	26.98	0.04	25.28	0.11	-1.70
Pork	27.29	0.13	27.90	0.56	0.61
Broilers	46.69	-0.20	47.11	-0.20	0.62
Turkey	5.55	-0.03	5.64	-0.01	0.09
Total Meat	107.06	-0.07	106.66	0.46	-0.40
Prices			($ per Cwt.)		
Steers	177.30	-1.18	185.00	-0.50	7.70
Hogs	59.70	-0.18	61.25	-3.50	1.55
			(Cents per Pound)		
Broilers	124.00	0.80	122.30	1.00	-1.80
Turkey	144.90	-4.60	137.80	-8.80	-7.10

Source: USDA-WAOB.

Table 2. Corn Supply and Use

Marketing Year		2022		2023		
		Estimate	**Change from September**	**Forecast**	**Change from September**	**Change from 2022 to 2023**
Area Planted	(mil. acres)	88.6	0.0	94.9	0.0	6.3
Yield	(bu./acre)	173.4	0.0	173.0	-0.8	-0.4
Production	(mil. bu.)	13,715	-15	15,064	-69	1,350
Beg. Stocks	(mil. bu.)	1,377	0	1,361	-90	-16
Imports	(mil. bu.)	39	-1	25	0	-14
Total Supply	(mil. bu.)	15,130	-16	16,451	-160	1,320
Feed & Residual	(mil. bu.)	5,549	124	5,600	-25	51
Ethanol	(mil. bu.)	5,177	-18	5,300	0	123
Food, Seed, & Other	(mil. bu.)	1,382	-28	1,415	0	33
Exports	(mil. bu.)	1,661	-4	2,025	-25	364
Total Use	(mil. bu.)	13,769	74	14,340	-50	571
Ending Stocks	(mil. bu.)	1,361	-90	2,111	-110	749
Season-Average Price	($/bu.)	6.54	-0.01	4.95	0.05	-1.59

Source: USDA-WAOB.

Note: Marketing year 2022 = 9/1/2022 to 8/31/2023.

Table 3. Soybean Supply and Use

Marketing Year		2022		2023		
		Estimate	Change from September	Forecast	Change from September	Change from 2022 to 2023
Area Planted	(mil. acres)	87.5	0.0	83.6	0.0	-3.9
Yield	(bu./acre)	49.6	0.0	49.6	-0.5	0.0
Production	(mil. bu.)	4,270	-6	4,104	-42	-166
Beg. Stocks	(mil. bu.)	274	0	268	18	-6
Imports	(mil. bu.)	25	-5	30	0	5
Total Supply	(mil. bu.)	4,569	-11	4,403	-24	-167
Crush	(mil. bu.)	2,212	-8	2,300	10	88
Seed & Residual	(mil. bu.)	97	-23	128	2	31
Exports	(mil. bu.)	1,992	2	1,755	-35	-237
Total Use	(mil. bu.)	4,301	-29	4,183	-23	-118
Ending Stocks	(mil. bu.)	268	18	220	0	-48
Season-Average Price	($/bu.)	14.20	0.00	12.90	0.00	-1.30

Source: USDA-WAOB.

Note: Marketing year 2022 = 9/1/2022 to 8/31/2023.

current projections for the 2023 and 2024 calendar years in the livestock sector. Overall, meat production in 2023 is set to be just slightly above 107 billion pounds. Compared to 2022, beef production declined, while pork, broiler, and turkey production increased. However, the overall total is slightly lower. Meat prices exhibit the opposite pattern, with higher beef prices and lower pork, broiler, and turkey prices. The outlook for 2024 points to lower beef production and increased pork, broiler, and turkey production. USDA expects beef prices to remain strong and projects pork prices will recover a bit. However, the forecast shows broiler and turkey prices will continue their decline. Total meat supplies will be lower, but there will be greater availability of pork and poultry. International meat trade is projected to rise slightly in 2024, as beef exports are projected to fall by 189 million pounds, but pork exports are expected to rebound by 189 million pounds along with roughly 100 million pounds of poultry export expansion.

For the corn and soybean markets, the September USDA report incorporates new acreage information from the Farm Service Agency and new survey data from NASS's farmer and objective yield queries. For both crops, USDA's new estimates indicate more acreage and less yield. The October report carried the acreage changes forward, but updated yield and production estimates. The national corn planted area estimate was increased by 800,000 acres to a total of 94.9 million acres; however, the national average corn yield estimate dropped to 173 bushels per acre. Putting together the acreage and yield updates, USDA finds evidence to keep supplies above 15 billion bushels for the year, which puts this year's production 1.35 billion bushels above the 2022 total and nearly equal to 2021 production.

USDA also updated corn usage (table 2). Given recent corn processing data, 18 million bushels were removed from the corn grind out of the 2022 crop. Corn export sales out of the 2022 crop were lowered by 4 million bushels and corn usage for sweeteners fell by 28 million bushels. However, corn feed and residual usage increased by 124 million bushels. Combining all of the changes, the projections show the 2022/23 corn ending stocks at 1.361 billion bushels. Normally, a reduction in stocks translates to an increase in prices, but USDA lowered its 2022/23 season-average price estimate by a penny to $6.54 per bushel. For the new (2023) crop, USDA reduced its estimates for feed and exports by 25 million bushels each, with feed and residual use at 5.6 billion bushels, ethanol at 5.3 billion bushels, food, seed, and other use at 1.415 billion bushels, and exports at 2.025 billion bushels. Overall corn usage is projected to be nearly 600 million bushels higher for the new corn marketing year—2023/24 ending stocks are now set at 2.111 billion bushels, down 110 million from last month, but up 749 million from last year. With plenty of corn available to the market, USDA estimates the 2023/24 season-average price at $4.95 per bushel.

Nationally, total planted area for soybeans increased from August's estimate by just under 100,000 acres, to 83.6 million acres (table 3). The national average soybean yield estimate came in at 49.6 bushels per acre, down 0.5 bushels. Overall, national soybean production is projected at 4.104 billion bushels. Soybean usage adjustments changed both domestic and international consumption. For the 2022 crop, exports were raised by 2 million bushels, reflecting slightly better sales at the end of the marketing year. On the other hand, domestic crush was reduced 8 million bushels and seed and residual usage fell by 23 million bushels. Those changes increased the 2022/23 ending stocks to 268 million bushels, maintaining already low stock levels. The 2022/23 season-average price estimate held steady at $14.20 per bushel. For the 2023 crop, the usage changes were mixed. The domestic crush expectation increased by 10 million bushels. The larger decline hit in exports, with 35 million bushels removed there, based on greater global supplies. Despite the reductions in usage, USDA projects 2023/24 ending stocks at 220 million bushels, down 48 million from last year. Thus, US soybean stocks are projected to get even tighter. Given the large global soybean supplies, it's not surprising that soybean prices are lower year-over-year. USDA has its 2023/24 season-average price estimate at $12.90 per bushel, $1.30 below last year.

Over the past couple years, US agriculture, for the most part, has enjoyed strong production, prices, exports, and incomes. The outlook going into 2024 shows reductions in most agricultural prices, a mixed picture in exports and production, and a decline in income. While incomes are retreating, the health of the overall agricultural economy is still good, it's just not quite as rosy as it used to be.

Suggested citation

Schulz, L., and C. Hart. 2023. "Agricultural Projections Going into 2024." Agricultural Policy Review Fall 2023. Center for Agricultural and Rural Development, Iowa State University. Available at: https://agpolicyreview.card.iastate.edu/fall-2023/agricultural-projections-going-2024.■

Linking Water Quality Improvement with Economic Benefits to the Iowa Population

Phil Gassman, Yongjie Ji, and Tássia Mattos Brighenti
pwgassma@iastate.edu; yongjiej@iastate.edu; tassiab@iastate.edu

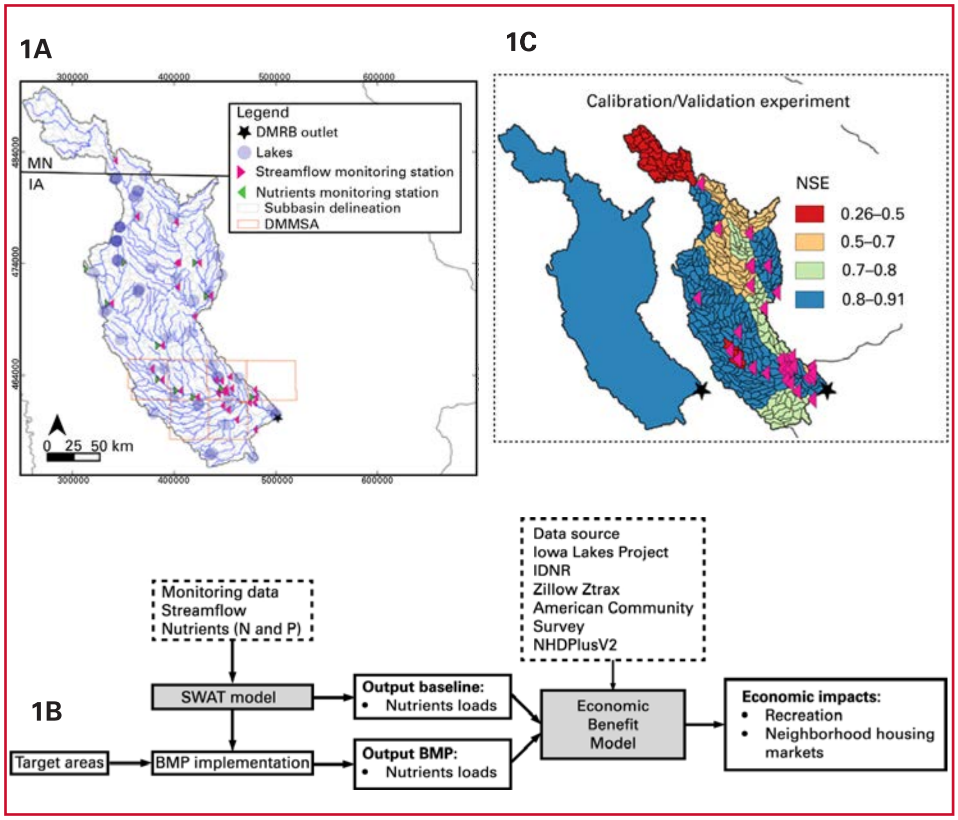

Figure 1a. Study area (Minnesota—MN; Iowa—IA) streamflow, nutrients monitoring gauge distribution, and lakes for the Des Moines River Basin. 1b. Flowchart showing the interface between SWAT and the EBM. 1c. Brighenti et al. (2023) SWAT model calibration/validation experiment.

Note: The left DMRB map shows the calibration results and the right DMRB map shows the validation results. A Nash-Sutcliffe efficiency (NSE) coefficient of ≥0.50 is a satisfactory model simulation (Moriasi et al. 2007; 2015).

THE IOWA Nutrient Reduction Strategy (INRS) establishes a goal of reducing nutrient discharge by 45% to Iowa streams and water bodies by 2035 (IDALS 2020), consistent with the nutrient reduction goal reported in the Gulf Hypoxia Action Plan (MRGMWN Task Force 2008). The INRS also embraced an interim Hypoxia Task Force goal to reduce nutrient losses 20% by 2025 (IDALS 2020). However, formidable challenges remain to attaining these goals as evidenced by pervasive elevated in-stream nitrogen (N) and phosphorus (P) levels in Iowa streams reported by Jones et al. (2018a; 2018b; 2019) and Schilling et al. (2020). Algal blooms have also been increasing in Iowa lakes and rivers, resulting in eutrophication, fish-kills, and harmful impacts on drinking water supplies, outdoor recreation, and tourism (IEC 2023; INRS 2023; Christianson et al. 2013). Mitigation of the seasonal hypoxic zone in the northern Gulf of Mexico, which is driven by nutrient export from the Mississippi River, has also proved elusive (Rabalais and Turner 2019).

We propose a methodology that integrates simulation models, pertinent data, and economic analysis to quantify the impacts of best management practices (BMPs) implementation on water quality and associated economic implications. Downing et al. (2021) state that economic studies of water quality regulations often report lower benefit estimates versus the costs, due in part to not understanding possible benefits of various ecosystem services. For example, new findings reveal that reducing N and P pollution in lakes and reservoirs not only reduces eutrophication, but also produces lower methane emissions that can impact the local and global climate (Downing et al. 2021).

Ecohydrological models can be used to test optimal management systems for cropland landscapes and to provide required inputs to economic models for both current and future nutrient reduction scenarios. In this study, we used the Soil and Water Assessment Tool (SWAT) model (https://swat.tamu.edu/), which has been applied worldwide for an extensive array of water resource problems (e.g., Akoko et al. 2021; Bressiani et al., 2015; Gassman et al. 2007, 2014; Tan et al. 2019; https://www.card.iastate.edu/swat_articles). SWAT's simulation structure can represent spatially refined estimations of water quality, resulting in the model's common use for simulation scenarios of changing land use, management conditions, and BMP implementation (Liu et al. 2019; Ricci et al. 2022; Secchi et al. 2007; Wang et al. 2019).

We developed an integrated assessment framework that features an interface between SWAT and an Economic Benefit Model (EBM) for the 31,892.4 km² Des Moines River Basin (DMRB) in central Iowa (figure 1a) to better understand the overall benefits of adopting different conservation practices. We chose the DMRB because: (*a*) it represents Iowa's typical corn and soybean cropping system cropland; (*b*) it provides water quality insights relevant to the Des Moines metropolitan area; (*c*) an extensive collection of monitoring data is available for streamflow, nitrate, and P; and, (*d*) the study area contains a total of 31 lakes, which are essential for validating the proposed methodology (figure 1a).

Study design

Figure 1b describes the framework that links the SWAT model and the EBM. Brighenti et al. (2022; 2023) describes the development of the SWAT model. We divide the DMRB into subbasins representative of the HUC12 (USGS 2022; 2023) discretization (figure 1c). We use the SWAT model monthly nutrient outputs from 2001 to 2018 to assess the impact of field buffers and cover crops, and a combination of the two practices (stacked). We select target areas for BMP implementation—corn and soybean fields—and our simulated practices target 100% of this rotational land use. Furthermore, we incorporate N and P loads into the EBM to evaluate the BMP impacts in terms of economic benefits on water quality improvements, recreation impacts, and housing market impacts.

Conservation practices

Mekonnen et al. (2015), Liu et al. (2019), Christianson et al. (2021), and Douglas-Mankin et al. (2021) establish the efficiency of field buffers and cover crops for reducing sediment and nutrient losses; and, modeling studies with SWAT, such as Kalcic et al. (2015), Merriman et al. (2018), and Motsinger et al. (2016), also show these practices effectively reduce pollutant losses. Iowa State University commonly recommends field buffers and cover crops for Iowa cropland landscapes (ISU 2022). Field buffers—strips of dense vegetation at the downslope boundary of a Hydrological Response Unit (HRU) in SWAT (for HRUs depicting a crop field)—intercept surface runoff. Field buffers remove contaminants by reducing overland flow and increasing infiltration area (Neitsch et al. 2011). We simulated field buffers in SWAT using White and Arnold's (2009) filter strip routine. Cover crops can increase soil moisture capacity, and reduce sediment loss, nutrient runoff, and leaching. We implemented cover crops between corn and soybean crop rotations in SWAT, which we model as cereal rye.

Table 1. Percentage of Nutrient Change per Implemented Scenario

SWAT output	Cover crop	Field buffer	Stacked
TN	-28%	-37%	-55%
TP	-22%	-65%	-70%
NO_3	-34%	-2%	-36%
Soluble P	+6%	-10%	-7%
Secchi	-1.5%	-14.8%	-17.7%

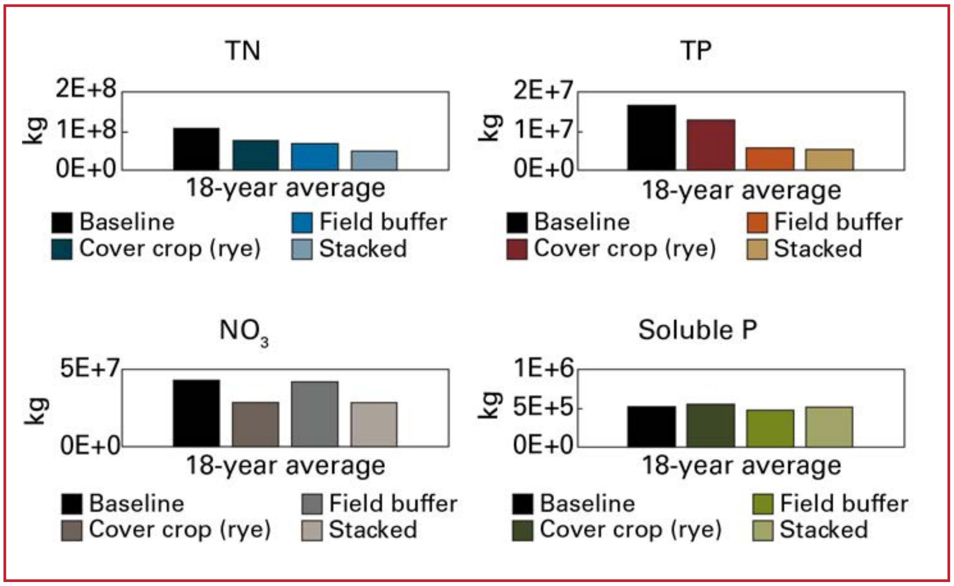

Figure 2. Eighteen-year change for BMP application considering nitrate (NO_3), total nitrogen in surface runoff (TN), soluble phosphorus (SP), and total phosphorus in surface runoff (TP).

Scenarios description

We executed the models for four distinct scenarios: (*a*) a baseline, which represents current conditions and is used in the practices comparison; (*b*) cover crops, which are the same as the baseline with rye crop planted during fall; (*c*) field buffers, which are the same as the baseline with the implementation of vegetative strips for corn and soybean

HRUs; and, (*d*) stacked, which is the implementation of cover crops and filter strips together. We applied the BMPs to 100% of the corn and soybean cropland HRUs in the DMRB.

Discussion

Scenario results

We executed the SWAT model to simulate the impact of BMP implementation on water quality over an 18-year period to capture long-term effects. We analyzed model outputs such as nutrient loads to evaluate the effectiveness of the BMPs. Figure 2 and table 1 present the total nitrogen in surface runoff (TN), total phosphorus in surface runoff (TP), nitrate (NO_3) and soluble phosphorus (SP) results for the three BMP scenarios (filter strips, cover crops, and stacked practices). We compare these results to the baseline scenario without BMP implementation.

Overall, stacked practices—combining two strategies (i.e., cover crops and field buffers)—generate the most efficient nutrient reduction, showing a 36% reduction in NO_3, a 55% reduction in TN, and a 70% reduction in TP. However, the reduction in SP was considerably less, showing only a 7% decrease in surface runoff. The field buffer was the second most effective scenario, showing a 2% reduction for NO_3, 10% for SP, 37% for TN, and 65% for TP. The small reduction for NO_3 is consistent with expectations (ISU 2022)—subsurface flow via tile drains transports the majority of NO_3, thus surface vegetation does not capture it. The cover crop scenario results in 37% and 22% reductions in TN and TP respectively, and is the most effective practice when considering just NO_3—a reduction of 34% (table 1 and figure 2). However, implementing cover crops results in a 6% increase of SP. This is consistent with a number of field studies as reported by Liu et al. (2019) and Nelson (2023), and underscores the need to consider all aspects of BMP effects when considering treatment approaches for a given watershed or region.

It is important to acknowledge that BMP efficiency in reducing N and P depends on several factors, including land use type, implementation scale, and the specific BMPs employed. Moreover, achieving significant nutrient reduction often requires a combination of BMPs, making it crucial to develop integrated approaches tailored to specific landscapes. For lake water quality analysis, the SWAT output of interest for the economic model is the TN and TP, which are used to compute the Secchi depth (table 1).

Table 2. Recreation Benefits (in millions)

	2002	2003	2004	2005	2009	2014	2019	Avg
				Cover Crop				
Total	4.231	1.952	0.201	3.501	-0.505	-0.019	-0.032	1.333
Research Area	1.236	0.556	0.084	1.183	-0.236	-0.090	-0.032	0.386
Other Counties	2.995	1.395	0.117	2.318	-0.269	0.071	-0.032	0.942
				Field Buffer				
Total	11.510	7.407	15.122	29.803	15.899	8.134	8.389	13.752
Research Area	3.556	2.351	5.040	9.490	5.768	2.317	2.378	4.414
Other Counties	7.954	5.056	10.082	20.313	10.131	5.817	6.011	9.338
				Stacked				
Total	12.869	13.142	21.012	34.804	18.482	9.838	11.624	17.396
Research Area	3.949	3.984	7.254	11.168	5.927	2.841	3.184	5.472
Other Counties	8.920	9.158	13.758	23.637	12.555	6.997	8.440	11.924

Table 3. Housing Benefits (in millions $)

	Primary Study				Benefit Transfer		
	Linear WQ		logarithm WQ		Guignet et al. (2022)		
	Secchi	TN	Secchi	TN	Secchi	TN	TP
			Cover Crop				
Total	0.061	0.595	0.104	0.240	0.232	1.943	2.142
Waterfront	0.044	0.595	0.104	0.240	0.192	1.223	1.928
Non-waterfront	0.017	-	-	-	0.039	0.720	0.214
			Field Buffer				
Total	0.926	3.464	1.452	0.307	3.288	2.534	2.329
Waterfront	0.666	3.464	1.452	0.307	2.683	1.562	2.099
Non-waterfront	0.260	-	-	-	0.604	0.972	0.229
			Stacked				
Total	1.531	0.975	1.800	0.468	4.121	3.819	2.347
Waterfront	1.038	0.975	1.800	0.468	3.326	2.381	2.116
Non-waterfront	0.493	-	-	-	0.795	1.438	0.231

Note: Waterfront: the housing parcel is within 100 meters from lake shores. Non-waterfront: the housing parcel is within 100 to 300 meters. We use a median house sale price of $212,075 to measure the housing price changes.

Economic model

Our recreation models suggest Secchi depth is the only water quality measure with consistently significant coefficients; thus, we picked one random forest machine learning model to convert TN and TP output from the SWAT models to lake Secchi depth. In the first stage, we train our random forest model with Iowa Department of Natural Resources' AQuIA database (https://programs.iowadnr.gov/aquia/) lake water quality data, such as TN, TP, and Secchi depth. In the second stage, we assume the TN and TP load changes in a HUC12 containing a lake as the changes from the baseline for each lake (based on the HUC12 in which the lake centroid is located). Table 1 also shows the model-predicted Secchi depth change in each scenario. The cover crop scenario produces the least improvement in Secchi depth, the field buffer scenario produces around 15% improvement, and, unsurprisingly, the stacked scenario implies the highest improvement (18%). The chosen random forest model shows the dominant effect of TP (i.e., lower TP equals better Secchi depth). Thus, the change in Secchi depth generally follows the ranking of TP reduction.

Recreation benefits

Table 2 shows recreation benefits in terms of compensating variation, a willingness-to-pay measure that indicates how much a person will pay for a given water quality change in our context. Our recreation model suggests that the highest benefit is associated with the stacked scenario since the Secchi depth improvement is the largest (table 1). The total benefit on average was around $17 million per year in the stacked scenario, followed by the field buffer scenario ($14 million) and the cover crop scenario ($1.3 million). Recreation benefits vary depending on which year of data we use. Ji et al. (2020) also find this temporal change, though our model here uses a slightly different model setting. Another observation is that though the improvement may happen in local lakes, the benefit spreads to other areas since local lakes attract households from other areas. CARD's Iowa Lakes Project reports that the median travel distance from Iowa households to surveyed lakes (included in our study) is in the range of 30–60 miles as of 2019 (Wan, Ji, and Zhang 2019).[1] In our specific case, the share of regional benefits is significant and larger than that of local benefits. On average, local benefits accounted for only one-third of the total benefit.

Housing benefit

To estimate the housing impacts, we rely on two approaches: our own hedonic model built on Zillow Ztrax database and Iowa DNR water quality data, and the benefit transfer method built on Guignet et al. (2022).

Our primary study is based on a multivariate regression function that uses house sale price adjusted to 2020 prices, a water quality measure, Secchi depth, TN, TP, and a set of control variables such as whether the property is 100 meters or less (waterfront) or between 100 and 300 meters (nearby) from a water body,[2] and includes typical house attributes such as building age, square footage, and number of bedrooms.[3] We keep residential houses within 500 meters from a lake shore in our study. We adapt our preparation of Ztrax data from scripts provided by Zillow on the GitHub repository (https://github.com/zillow-research/ztrax).[4] Once we have the estimated hedonic functions, we find the possible impacts of water quality change under different scenarios.

Guignet et al. (2022) provide the necessary unit elasticity information to conduct the benefit calculation and summarize these elasticities from their meta-regression model built on more than 20 individual hedonic studies on lake water quality. We choose the elasticities associated with TN, TP, and Secchi depth for our work.

Table 3 provides a summary of housing impacts under three SWAT scenarios. Several observations stand out. First, both our primary study and the benefit transfer approach detect the housing impacts under different scenarios, which, in almost all cases, agree with the impact direction. Second, the magnitude of the impacts differs between these two approaches. Third, within each approach, the impacts vary in response to which form of water quality measure we account for. Fourth, the majority of impacts come from the waterfront houses in most cases. With current estimates, it seems the specification with the linear Secchi depth in our primary study produces the closest estimates to the results from the benefit transfer approach with Secchi depth as the target water quality measure.

Using the annual average of recreation benefits and the housing benefit from the linear Secchi depth in our primary study, the stacked scenario produces the highest benefit with a total of about $19 million per year followed by the field buffer scenario ($15 million), then the cover crop scenario ($1.5 million).[5]

Rosen (1974) lays the theoretical foundation for the hedonic model to investigate the relationship between house prices and house attributes. However, the theory is quite silent on the specification and the form of house attributes included in the model. Thus, we expected the discrepancy shown in table 3. This creates a challenge for researchers in terms of how to choose the metric to quantify the benefits. An internal-meta analysis suggested in Klemick et al. (2018) would be useful here to know more about the uncertainties.[6]

Conclusion and future considerations

The methodology and preliminary results presented here demonstrate the possibility of implementing an

---

1. Interested readers can visit www.card.iastate.edu/lakes to learn more about our Iowa Lakes Project work and related concepts.
2. Our choice of cutoff distance follows Mamun et al (2023).
3. Formula available upon request.
4. Our hedonic analysis only has preliminary results at this stage. Interested readers can email yongjiej@iastate.edu for the current model result and progress.
5. We use one-twentieth of the total housing benefits as the shortcut to annualize the total effect.
6. This is our second stage of work.

integrated framework between SWAT and economic valuation models to study both environmental impacts and economic impacts of the adoption of BMPs at regional scale. More extensive calibration and validation of baseline SWAT sediment and nutrient loads is needed, along with accounting for a more complete set of BMPs. In addition, better economic evaluation models need to be developed to provide a more complete analysis of benefits associated with water quality. Overall, we believe this framework can contribute to water quality improvement programs and offer valuable information for researchers and stakeholders working in the field.

References

Akoko, G., T.H. Le, T. Gomi, and T. Kato. 2021. "A Review of SWAT Model Application in Africa." Water (Switzerland) 13. https://doi.org/10.3390/w13091313.

Arnold, J.G., D.N. Moriasi, P.W. Gassman, K.C. Abbaspour, M.J. White, R. Srinivasan, C. Santhi, R.D. Harmel, A. Van Griensven, M.W. VanLiew, N. Kannan, and M.K. Jha. 2012. "SWAT: Model Use, Calibration, and Validation." Transactions of the ASABE 55:1491–1508. https://elibrary.asabe.org/abstract.asp?aid=42256.

Bressiani, D. de A., P.W. Gassman, J.G. Fernandes, L.H.P. Garbossa, R. Srinivasan, N.B. Bonumá, and E.M. Mendiondo. 2015. "A Review of Soil and Water Assessment Tool (SWAT) Applications in Brazil: Challenges and Prospects." International Journal of Agricultural Biological Engineering 8:1–27. https://doi.org/10.3965/j.ijabe.20150803.1765.

Brighenti, T.M., P.W. Gassman, K.E. Schilling, R. Srinivasan, M. Liebman, and J.R. Thompson. 2022. "Determination of Accurate Baseline Representation for three Central Iowa Watersheds within a HAWQS-based SWAT Analyses." Science of the Total Environment 839. https://doi.org/10.1016/j.scitotenv.2022.156302.

Brighenti, T.A., P.W. Gassman, J. Arnold, and J.R. Thompson. 2023. SWAT Model Comparison Between Two Methods for Calculating Tile-Drain Flow Via Spatial and Temporal Calibration. Tile drain." Transactions of the ASABE. (In review)

Christianson, R., J. Fox, N. Law, and C. Won. 2021. "Effectiveness of Cover Crops for Water Pollutant Reduction from Agricultural Areas." Transactions of the ASABE 64(3):1007–1017. https://doi.org/10.13031/trans.14028.

Christianson, L., J. Tyndall, and M. Helmers. 2013. "Financial Comparison of Seven Nitrate Reduction Strategies for Midwestern Agricultural Drainage." Water Resources and Economics 2–3:30–56. https://doi.org/10.1016/j.wre.2013.09.001.

Douglas-Mankin, K.R., M.J. Helmers, and R.D. Harmel. 2021. "Review of Filter Strip Performance and Function for Improving Water Quality from Agricultural Lands." Transactions of the ASABE 64(2):659–674. https://doi.org/10.13031/trans.14169.

Downing, J.A., S. Polasky, and S.M. Olmstead. 2021. "Protecting Local Water Quality Has Global Benefits." Nature Communications 12:2709. https://doi.org/10.1038/s41467-021-22836-3.

Gassman, P.W., M.R. Reyes, C.H. Green, and J.G. Arnold. 2007. "The Soil and Water Assessment Tool: Historical Development, Applications, and Future Research Directions." Transactions of the ASABE 50:1211–1250. https://doi.org/10.1.1.88.6554.

Gassman, P.W., A.M. Sadeghi, and R. Srinivasan. 2014. "Applications of the SWAT Model (Special Section): Overview and Insights." Journal of Environmental Quality 43:1. https://doi.org/10.2134/jeq2013.11.0466.

Guignet, D., M.T. Heberling, M. Papenfus, and O. Griot. 2022. "Property Values, Water Quality, and Benefit Transfer: A Nationwide Meta-analysis." Land Economics 98(2):191–218. https://doi.org/10.3368/le.98.2.050120-0062r1.

Iowa Environmental Council (IEC). 2023. Water and Land Publications: Iowa Nutrient Reduction Strategy: Policy Solutions to Actually Reduce Nutrient Pollution in Iowa's Water. https://www.iaenvironment.org/webres/File/NRS 2_0-Policy Solutions to Reduce Nutrient Pollution in Iowa's Water.pdf.

Iowa Department of Agriculture and Land Stewardship (IDALS). 2020. Iowa Nutrient Reduction Strategy: 2018-19 Annual Progress Report. Iowa Department of Agriculture and Land Stewardship, Des Moines, IA (in collaboration with the Iowa Department of Natural Resources, Des Moines, IA and Iowa State University). https//www.nutrientstrategy.iastate.edu/documents.

Iowa Nutrient Reduction Strategy (INRS). 2023. Iowa Nutrient Reduction Strategy: Strategy documents. Available at: https://www.nutrientstrategy.iastate.edu/sites/default/files/documents/2017 INRS Complete_Revised 2017_12_11.pdf.

Iowa State University (ISU). 2022. Whole Farm Conservation Best Practices Manual. Iowa State University, Extension and Outreach, Ames, IA. https://store.extension.iastate.edu/product/Whole-Farm-Conservation-Best-Practices-Manual.

Ji, Y., D.A. Keiser, and C.L. Kling. 2020. "Temporal Reliability of Welfare Estimates from Revealed Preferences." Journal of the Association of Environmental and Resource Economists 7(4):659–686. https://doi.org/10.1086/708662.

Jones, C.S., C.W. Drake, C.E. Hruby, K.E. Schilling, and C.F. Wolter. 2019. "Livestock Manure Driving Stream Nitrate." Ambio 48(10):1143–1153. https://doi.org/10.1007/s13280-018-1137-5.

Jones, C.S., J.K. Nielsen, K.E. Schilling, and L.J. Weber. 2018a. "Iowa Stream Nitrate and the Gulf of Mexico." PLoS ONE 13(4):e0195930. https://doi.org/10.1371/journal.pone.0195930.

Jones, C.S., K.E. Schilling, I.M. Simpson, and C.F. Wolter. 2018b. "Iowa Stream Nitrate, Discharge and Precipitation: 30-year Perspective." Environmental Management 62(4):709–720. https://doi.org/10.1007/s00267-018-1074-x.

Kalcic, M.M., J. Frankenberger, and I. Chaubey. 2015. "Spatial Optimization of Six Conservation Practices Using Swat in Tile-Drained Agricultural Watersheds." Journal of the American Water Resources Association 51(4):956–972. https://doi.org/10.1111/1752-1688.12338.

Klemick, H., C. Griffiths, D. Guignet, and P. Walsh. 2018. "Improving Water Quality in an Iconic Estuary: An Internal Meta-analysis of Property Value Impacts around the Chesapeake Bay." Environmental and Resource Economics 69:265–292. https://doi.org/10.1007%2Fs10640-016-0078-3.

Liu, J., M.L. Macrae, J.A. Elliott, H.M. Baulch, H.F. Wilson, and P.J.A. Kleinman. 2019. "Impacts of Cover Crops and Crop Residues on Phosphorus Losses in Cold Climates: A Review." Journal of Environmental Quality 48:850–868. https://dx.doi.org/10.2134/jeq2019.03.0119.

Liu, Y., R. Wang, T. Guo, B.A. Engel, D.C. Flanagan, J.G. Lee, S. Li, B.C. Pijanowski, P.D. Collingsworth, and C.W. Wallace. 2019. "Evaluating Efficiencies and

Cost-effectiveness of Best Management Practices in Improving Agricultural Water Quality using Integrated SWAT and Cost Evaluation Tool." Journal of Hydrology 577:123965. https://doi.org/10.1016/j.jhydrol.2019.123965.

Mamun, S., A. Castillo-Castillo, K. Swedberg, J. Zhang, K.J. Boyle, D. Cardoso, C.L. Kling, C. Nolte, M. Papenfus, D. Phaneuf, and S. Polasky. 2023. "Valuing Water Quality in the United States using a National Dataset on Property Values." Proceedings of the National Academy of Sciences 120(15):p. e2210417120. https://doi.org/10.1073/pnas.2210417120.

Mekonnen, M., S.D. Keesstra, L. Stroosnijder, J.E.M. Baartman, and J. Maroulis. 2015. "Soil Conservation through Sediment Trapping: A Review." Land Degradation & Development 26(6):531–628. https://dx.doi.org/10.1002/ldr.2308.

Mississippi River/Gulf of Mexico Watershed Nutrient Task Force (MRGMWN Task Force). 2008. Gulf Hypoxia Action Plan 2008 for Reducing, Mitigating, and Controlling Hypoxia in the Northern Gulf of Mexico and Improving Water Quality in the Mississippi River Basin. https://www.epa.gov/ms-htf/gulf-hypoxia-action-plan-2008.

Moriasi, D.N., J.G. Arnold, M.W. Van Liew, R.L. Binger, R.D. Harmel, and T.L. Veith. 2007. "Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations." Transactions of the ASABE 50:885–900. https://doi.org/10.13031/2013.23153.

Moriasi, D.N., M.W. Gitau, N. Pai, and P. Daggupati. 2015. "Hydrologic and Water Quality Models: Performance Measures and Evaluation Criteria." Transactions of the ASABE 58:1763–1785. https://doi.org/10.13031/trans.58.10715.

Merriman, K.R., P. Daggupati, R. Srinivasan, C. Toussant, A.M. Russell, and B. Hayhurst. 2018. "Assessing the Impact of Site-Specific BMPs Using a Spatially Explicit, Field-Scale SWAT Model with Edge-of-Field and Tile Hydrology and Water-Quality Data in the Eagle Creek Watershed, Ohio." Water 10:1299. https://doi.org/10.3390/w10101299.

Motsinger, J., P. Kalita, and R. Bhattarai. 2016. "Analysis of Best Management Practices Implementation on Water Quality Using the Soil and Water Assessment Tool." Water 8:145. https://doi.org/10.3390/w8040145.

Nelson, N. 2023. Cover Crop Impacts on Surface Runoff, Sediment and Phosphorus Losses. Iowa Learning Farms, Iowa State University, Ames, IA. https://www.iowalearningfarms.org/resources/-nathan-nelson.

Neitsch, S.L., J.G. Arnold, J.G. Kiniry, and J.R. Williams. 2011. Soil and Water Assessment Tool Theoretical Documentation: Version 2009. U.S. Department of Agriculture – Agricultural Research Service, Grassland, Soil and Water Research Laboratory, Temple, TX and Blackland Research and Extension Center, Texas AgriLife Research, Temple, Texas. Texas Water Resources Institute Technical Report No. 406, 618 pp. http://swatmodel.tamu.edu/documentation/.

Rabalais, N.N., and R.E. Turner. 2019. "Gulf of Mexico Hypoxia: Past, Present, and Future." Limnology and Oceanography Bulletin 28(4):117–124. https://doi.org/10.1002/lob.10351.

Ricci, G.F., E. D'Ambrosio, A.M. De Girolamo, and F. Gentile. 2022. "Efficiency and Feasibility of Best Management Practices to Reduce Nutrient Loads in an Agricultural River Basin." Agricultural Water Management 259:107241. https://doi.org/10.1016/j.agwat.2021.107241.

Rosen, S., 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." Journal of Political Economy 82(1):34–55. https://www.jstor.org/stable/1830899.

Secchi, S., P.W. Gassman, M. Jha, L. Kurkalova, H.H. Feng, T. Campbell, and C.L. Kling. 2007. "The Cost of Cleaner Water: Assessing Agricultural Pollution Reduction at the Watershed Scale." Journal of Soil and Water Conservation 62:10–21. https://www.jswconline.org/content/62/1/10.

Schilling, K.E., M.T. Streeter, A. Seeman, C.S. Jones, and C.F. Wolter. 2020. "Total Phosphorus Export from Iowa Agricultural Watersheds: Quantifying the Scope and Scale of a Regional Condition." Journal of Hydrology 581:124397. https://doi.org/10.1016/j.jhydrol.2019.124397.

Tan, M.L., P.W. Gassman, R. Srinivasan, J.G. Arnold, and X.Y. Yang. 2019. "A Review of SWAT Studies in Southeast Asia: Applications, Challenges and Future Directions." Water (Switzerland) 11:1–25. https://doi.org/10.3390/w11050914.

United States Geological Service (USGS). 2022. "Federal Standards and Procedures for the National Watershed Boundary Dataset (WBD). Techniques and Methods. Federal Standards Book 11, Collection and Delineation of Spatial Data, Fifth Edition. US Department of the Interior, US Geological Survey, Reston, VA and US Department of Agriculture, Natural Resources Conservation Service, Washington, DC, 54 pp. https://doi.org/10.3133/tm11a3.

United States Geological Service (USGS). 2023. Hydrologic Unit Codes (HUCs) Explained. US Department of the Interior, US Geological Survey, Reston, VA. https://nas.er.usgs.gov/hucs.aspx.

Wan, X., Y. Ji, and W. Zhang. 2019. "A Report to the Iowa Department of Natural Resources. The Iowa Lakes Valuation Project 2019: Summary and Findings." Staff report 21-SR 115. Center for Agricultural and Rural Development, Iowa State University. Available at: https://www.card.iastate.edu/lakes/data/surveys/iowa_lakes_survey_report_2019.pdf.

Wang, Y., J. Bian, W. Lao, Y. Zhao, Z. Hou, and X. Sun. 2019. "Assessing the Impacts of Best Management Practices on Nonpoint Source Pollution Considering Cost-effectiveness in the Source area of the Liao River, China." Water (Switzerland) 11:1–20. https://doi.org/10.3390/w11061241.

White, M.J., and J.G. Arnold. 2009. "Development of a Simplistic Vegetative Filter Strip Model for Sediment and Nutrient Retention at the Field Scale." Hydrological Processes 23(11):1602–1616. https://doi.org/10.1002/hyp.729.

Suggested citation

Gassman, P., Y. Ji, and T.M. Brighenti. 2023. "Linking Water Quality Improvement with Economic Benefits to the Iowa Population." Agricultural Policy Review Fall 2023. Center for Agricultural and Rural Development, Iowa State University. Available at: https://agpolicyreview.card.iastate.edu/fall-2023/linking-water-quality-improvement-economic-benefits-iowa-population.■

Solar Energy Surge in Iowa: Policies, Public Opinions, and Future Opportunities

Jian Chen, Hongli Feng, Elizabeth Hoffman, and Luke Seaberg
chenjian@iastate.edu; hfeng@iastate.edu; bhoffman@iastate.edu; seaberg@iastate.edu

IN 2022, Iowa ranked first in the United States for percentage of state electricity produced by wind energy, which contributed 62% of its net electricity generation (USEIA 2023a). In contrast, in 2023, Iowa ranks 34th in solar generation, which represents only 1% of its total electricity generation (Glover 2023).

Over the past two decades, solar energy systems have improved in efficiency and declined in cost of installation. At present, solar energy represents the most economical option for electricity generation based on the metrics of the average levelized cost of energy (USEIA 2023b). Given the availability and consistency of high-quality solar natural resources across Iowa, coupled with its cost-effectiveness, solar energy can play a crucial role in attaining Iowa's established goal of reaching 100% clean power by 2035 (IEC 2021) and further driving down electricity rates.

This article briefly explores the development of solar energy systems in Iowa, describes a range of policies concerning solar energy development at the federal and local levels, and summarizes a sample of Iowans' preferences for and interest in solar energy systems.

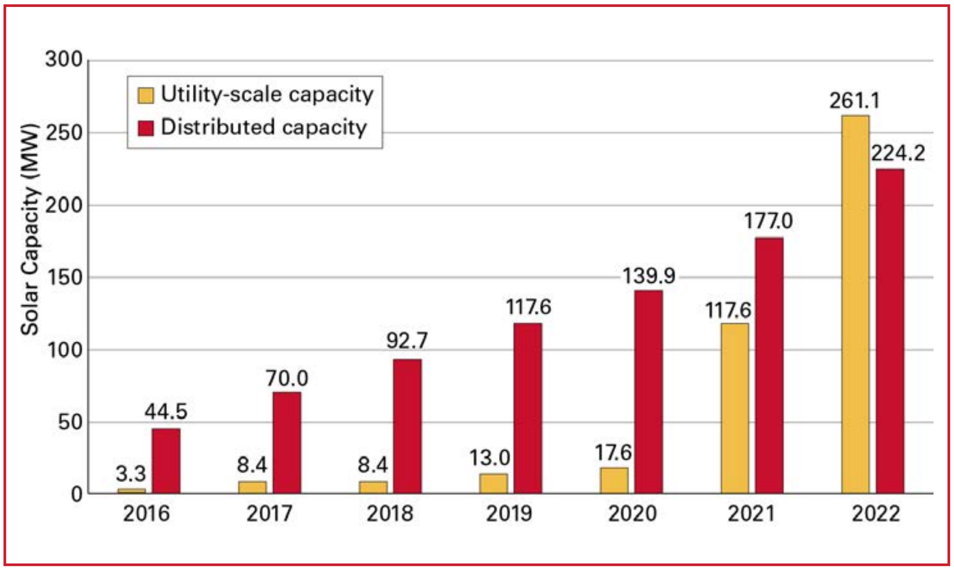

Figure 1. Nameplate capacity of solar energy systems in Iowa (2016–2022).
Source: Inventory of Operating Generators (2023), and Electric Power Monthly (2016–2022), US Energy Information Administration.

An overview of solar energy systems in Iowa

Iowa's first operable utility-scale solar photovoltaic (PV) power plant, the Cedar Falls Solar Farm in Black Hawk County, went online in April 2016 with an electricity generation capacity of 1.5 megawatts (MW). Prior to 2016, distributed facilities aimed at satisfying individual power needs produced the only solar PV power in Iowa. However, as shown in figure 1, between 2016 and 2022, Iowa experienced rapid growth in utility-scale solar energy, with the commissioning of 16 utility-scale solar PV power plants and total nameplate capacity growing from 3.3 MW to 261.1 MW. Throughout the same period, Iowa averaged a 33% annual increase in distributed solar energy systems, which expanded from 44.5 MW to 224.2 MW.

Based on ownership structures, we can categorize utility companies into three main types: investor-owned, municipal, and cooperative. Investor-owned utilities are typically driven by profit motives, municipal utilities are community owned and prioritize local interests, and cooperatives are democratically governed by their members. In 2022, 16 utility-scale solar PV power plants were in operation: 8 by investor-owned utilities, 5 by municipal utilities, and 3 by cooperatives. These operable utility-scale solar PV power plants had a combined capacity of 147.6 MW for investor-owned utilities, 108.5 MW for municipal utilities, and 5 MW for cooperatives. The Energy Information Administration categorizes distributed solar facilities by sectors based on where and how customers utilize the energy. By 2022, Iowa had distributed solar installations with capacities of 116.8 MW in the residential sector, 126.5 MW in the commercial sector, and 9.9 MW in the industrial sector, which indicates that solar growth has happened under all ownership structures.

Figure 2 depicts the distribution of utility-scale and distributed solar PV capacities in Iowa as of 2020. Aggregated at the county level, a total of 13 counties had distributed solar PV capacity greater than 1 MW, the threshold level often used to define a utility-scale power plant. The geographical distribution of distributed solar PV capacity has high spatial alignment with the allocation of Iowa cities (i.e., the state's population centers). To be specific, among Iowa counties, Black Hawk, Polk, and Linn were the top three in distributed solar installation in 2020 with capacities of 9.8 MW, 6.4 MW, and 5.3 MW, respectively. At that time, the average capacity per county in Iowa was 0.6 MW.

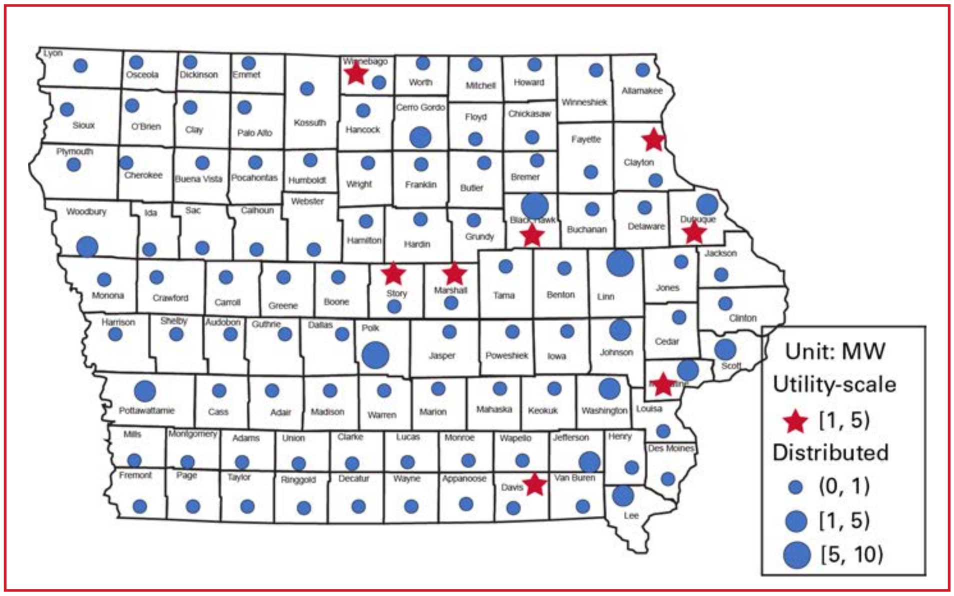

Figure 2. Distribution of utility-scale and distributed solar PV capacities in Iowa, 2020.

Source: Utility-scale solar PV capacity data is from the US Energy Information Administration Inventory of Operating Generators (2023); Distributed solar PV capacity is from the Open Energy Data Initiative, Lawrence Berkeley National Laboratory.

Note: Lawrence Berkeley National Laboratory did not report the installed capacity of distributed solar energy at the county level for the years following 2020.

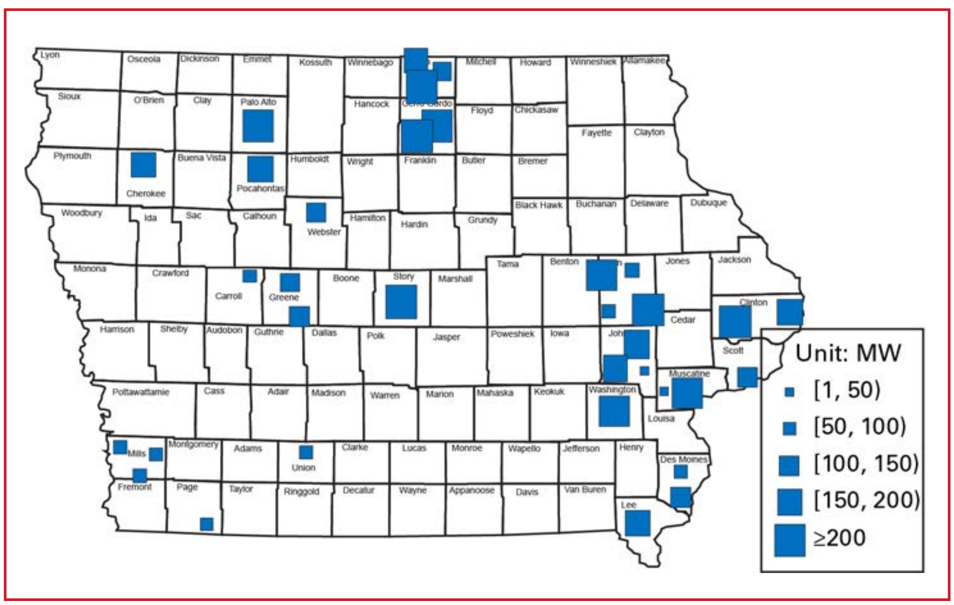

Figure 3. Midcontinent Independent System Operator queue solar projects.

Source: Midcontinent Independent System Operator public interconnection queue dataset, accessed August 2023.

Utility-scale solar energy in Iowa continues growing at an accelerating pace. According to the Midcontinent Independent System Operator public interconnection queue, as of August 2023, there are 34 utility-scale solar PV projects in the pipeline. Of these, 7 are under construction, and 27 are at the planning and investigation stage. These proposed utility-scale solar projects vary significantly in generation capacity, ranging from 1.4 MW to 400 MW, with a combined nameplate capacity of 4,634 MW. This represents a 17.7-fold increase compared with the 2022 level. Figure 3 shows the location and capacity of the proposed utility-scale solar PV projects. Notably, these proposed projects are mostly located in the regions that are close to or within proximity of Iowa's population centers, where the demand for electricity is higher than in more rural areas. Locating solar projects near these population centers can reduce transmission costs and make it easier to deliver clean energy to customers. While data on future rooftop solar installations in Iowa is unavailable, Wood Mackenzie forecasts an average annual growth rate of 8% for rooftop solar installations across the nation between 2025 and 2028 (SEIA 2023b).

Federal and state policies and incentives

Solar energy, both utility-scale and distributed, has received and will continue to receive substantial support at the federal and local levels. According to the Database of State Incentives for Renewables Efficiency, as of August 2023, Iowa has seven active state-level programs, including financial incentives and regulatory policies, that are applied to solar PV energy. Most of these programs (i.e., five out of the seven) primarily target

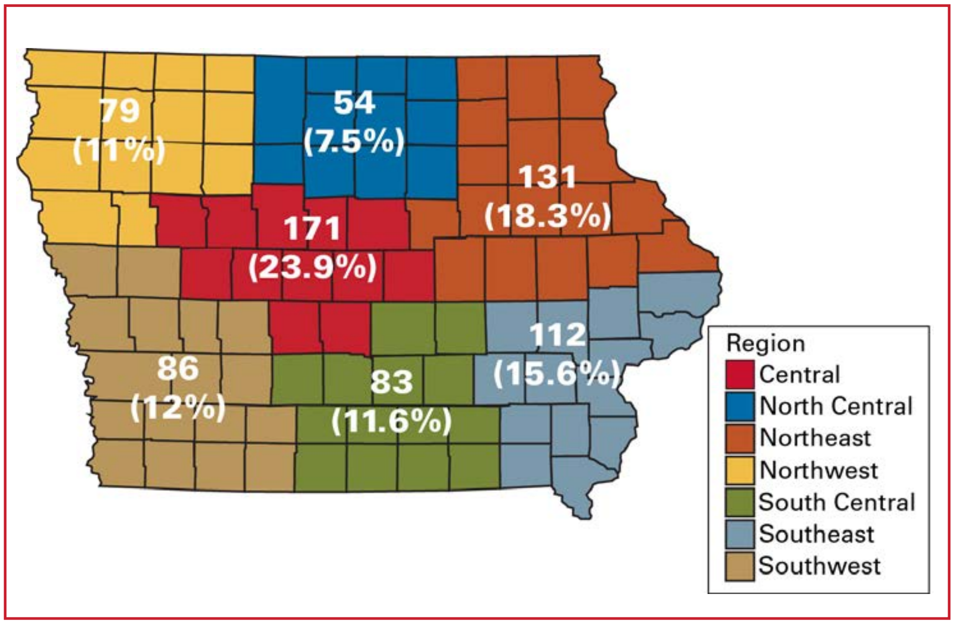

Figure 4. Regional distribution of survey responses.

Note: The division of regions follows the classification used by the Iowa League of Cities.

distributed solar energy with support and incentives related to sales taxes, access policies, property taxes, net metering, and interconnection. Additionally, there are two active programs supporting utility-scale solar energy development: the renewable portfolio standards and the mandatory utility green power option. In 1983, Iowa became the first US state to establish Renewable Portfolio Standards, and met its target of 105 MW renewable energy generation capacity in 1997 (NREL 2013). At the federal level, there are 16 active programs, including four geared towards utility-scale solar energy systems in the form of grants and green power purchasing options. Eleven of these initiatives are applicable to distributed solar energy systems related to corporate tax exemptions/credits, personal tax exemptions, corporate depreciation, interconnection, loan programs, and grant programs. Furthermore, there is one program, the corporate tax credit, that applies to both types of solar energy systems.

The most notable federal policy is the 2022 Inflation Reduction Act (IRA). This act extends and enhances several tax incentives and credits for both types of solar installations. Specifically, the IRA extends the existing production tax credit (PTC) and investment tax credit (ITC) for eligible renewable energy sources, and introduces a new tech-neutral clean electricity PTC and ITC set to take effect in 2025. The new clean electricity PTC provides a credit of 1.5 cents per kWh for electricity produced, sold, or stored at facilities placed into service after 2024, provided they have zero or negative GHG emissions. Meanwhile, the clean electricity ITC offers a 30% credit of the investment in the year the facility is commissioned, allowing small projects under 5 MW to include interconnection costs. Moreover, until 2034, the IRA also will provide a 30% tax credit for residential and commercial solar projects. As projected by SEIA (2023a), the IRA is expected to result in 48% more solar development over the next 10 years than would have occurred without it. As to the impacts in Iowa specifically, Miller (2023) suggests that the IRA has fueled a growing interest in distributed solar energy in the state, with the number of interested customers increasing between 10% and 100%, depending on the power company.

Public perspectives on solar energy in Iowa

Public opinions on solar energy vary considerably. Advocates argue that solar power holds great potential for a clean energy future due to its ability to harness abundant sunlight, reduce emissions, create local jobs, and contribute to energy independence and stability. However, there is also opposition to solar energy mostly due to concerns over land use, aesthetics, and potential negative environmental impacts. Some argue that large solar farms alter rural landscapes and agricultural practices, while others raise questions about the disposal of PV panels at the end of the life of a solar project and their overall environmental footprint.

These contrasting views are evident in Iowa. While utility-scale solar energy has rapidly developed in Iowa, residents' opposition to it has garnered headlines in some regions. For instance, concerns about aesthetics and potential impacts on agriculture have led residents in the cities of Coggon and Palo to resist large-scale solar projects coming to Linn County (Payne 2021). In another instance in 2021, the Palo City Council voted to oppose NextEra Energy Resources' plans for a 1,780-acre solar farm located between Palo and Pleasant Creek. However, the project gained approval from Linn County supervisors in 2022, leaving city officials and residents frustrated with the decision (DMR 2023).

General public practices and preferences on solar energy systems in Iowa

To further investigate the general public's preferences regarding various types of solar energy systems, including rooftop and utility-scale solar, we conducted an online survey related to solar and land uses in Iowa. We distributed a total of 1,552 survey invitations to Iowa's general public and received 716 completed responses, a 46.1% response rate. Figure 4 shows the regional distribution of the survey responses, closely reflecting the population distribution across regions in Iowa.

Our survey findings reveal a relatively consistent pattern of rooftop solar participation across various regions within Iowa. As shown in figure 5, a small percentage of respondents reported that they have installed solar panels at their place of residence. Among these regions, the Northeast, North Central, and Southeast regions exhibit the highest rates of rooftop solar adoption, with participation rates of 7%–8%. For those respondents who have not yet adopted rooftop solar systems but are open to the idea in the near future, we found the percentage of respondents who are willing to adopt rooftop solar (18%–27%) is much higher than the actual participation rates (figure 5). In other words, there seems to be great unrealized potential in rooftop solar adoption across Iowa regions, likely driven by increasing awareness of the economic and environmental benefits of solar energy, as well as local incentives to promote rooftop solar adoption.

On the one hand, utility-scale solar projects hold great potential in meeting electricity demand and reducing dependency on fossil fuels. On the other hand, utility-scale solar projects also have significant impacts on surrounding landscapes and communities and there can be very different attitudes towards utility-scale solar. Such attitudes will be critical in determining whether a community will host a solar project. When asked "How strongly do you support your jurisdiction hosting utility-scale solar projects?" there are some regional differences in the degree of support; however, the majority of the respondents answered "Moderately," "Very," or "Extremely" in all regions (figure 6). Our survey is consistent with the survey conducted by the Tarrance Group in 2022, which shows that the majority (68%) of respondents of Iowa voters support new solar projects (BFI 2022). Respondents that indicate they

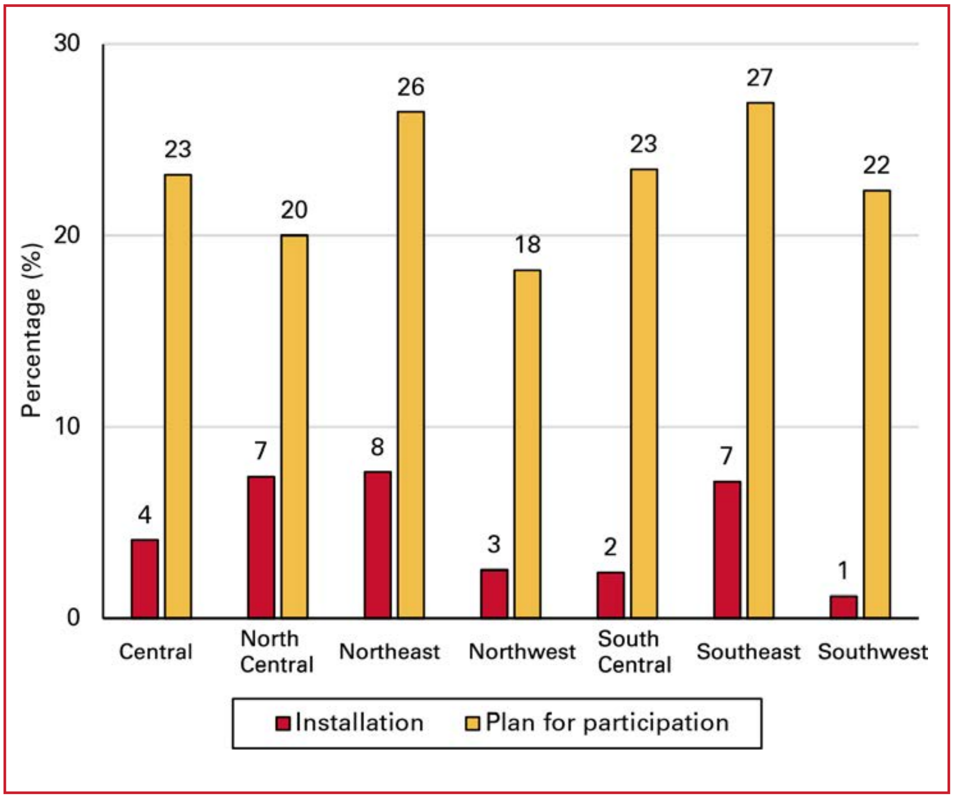

Figure 5. Installation of rooftop solar and plan for participation at the place of residence.

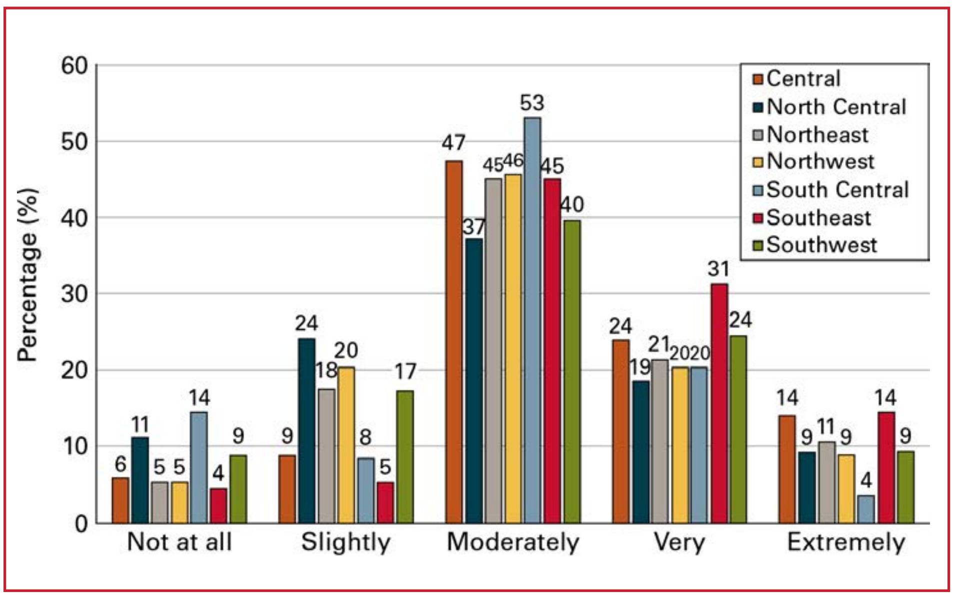

Figure 6. Support for hosting utility-scale solar projects in local communities by region.

do not support hosting utility-scale solar projects account for less than 10% of all respondents in five of the seven regions. In the two remaining regions, non-supporters account for 11% and 14% of respondents. Despite the regionally similar trends, there are some differences. For example, the Southeast region has the most respondents (45%) very strongly or extremely strongly supporting hosting solar versus 24% of respondents in the South-Central region.

As to the drivers and challenges

of utility-scale solar, our survey results suggest that respondents rate-reduced electricity bills as the most significant driver associated with the adoption of utility-scale solar projects within local communities (35%), closely followed by reduced carbon and other air pollutant emissions (32%). Meanwhile, about 32% of the respondents identified land use concerns, specifically the potential loss of farmland, as the primary challenge associated with the adoption of utility-scale solar energy systems, with an additional 31% expressing concerns about high initial investment costs, including construction costs. These regional differences are likely to determine the spatial adoption patterns of solar energy in Iowa in the near future.

To summarize, Iowa has experienced significant growth in solar energy development in recent years, and this trend is expected to accelerate further. Policy support, especially the Inflation Reduction Act of 2022, and technological advancement have made solar energy more cost competitive. This expansion has the potential to not only diversify the state's electricity landscape but also to keep the state's electricity rates among the lowest in the nation. Nevertheless, diverse perspectives on the benefits and costs of solar energy exist among residents, communities, and the state, implying tough decisions regarding its development and prioritization. Our survey-based findings reveal that while residents show significant interest and support for solar energy development, particularly in utility-scale projects, the current participation rate in rooftop solar is actually much lower than the expressed interest of Iowa residents. This discrepancy underscores the opportunities and potential for further solar energy expansion in Iowa.

References

Bright Future Iowa (BFI). 2022. "The Tarrance Group Survey Memo." Available at https://brightfutureiowa.com/wp-content/uploads/2022/02/Iowa-Summary-Memo_final-Copy.pdf.

Des Moines Register (DMR). 2023. "Iowa Residents Contend Solar, Wind Projects Get in the Way of Their Communities' Growth." Des Moines Register March 7, 2023. Available at https://www.desmoinesregister.com/story/money/agriculture/2023/03/07/iowa-wind-solar-farms-opposition-prompt-statewide-restrictions-legislature/69924871007/.

Glover, E. 2023. "The Best and Worst States for Solar Energy 2023." Forbes February 24, 2023. Available at https://www.forbes.com/home-improvement/solar/best-worst-states-solar/.

Iowa Environmental Council (IEC). 2021. "Council Sets Goal to Reach 100% Clean Power in Iowa by 2035." Available at https://www.iaenvironment.org/newsroom/energy-news/council-sets-goal-to-reach-100-clean-power-in-iowa-by-2035#.

Miller, J.B. 2023. "Inflation Reduction Act Creating 'Uptick' in Interest for Iowa Solar." The Gazette April 9, 2023. Available at https://www.thegazette.com/energy/inflation-reduction-act-creating-uptick-in-interest-for-iowa-solar/.

National Renewable Energy Laboratory (NREL). 2013. "Iowa State Summary: EERE Investment in Iowa." Available at https://www.nrel.gov/docs/fy13osti/57712.pdf.

Payne, K. 2021. "Utility-scale Solar Project Draws Opposition from Some Linn County Residents." Iowa Public Radio November 30, 2021. Available at https://www.iowapublicradio.org/ipr-news/2021-11-30/utility-scale-solar-project-draws-opposition-from-some-linn-county-residents.

Solar Energy Industries Association (SEIA). 2023a. "Impact of the Inflation Reduction Act." Available at https://www.seia.org/research-resources/impact-inflation-reduction-act.

Solar Energy Industries Association (SEIA). 2023b. "Solar Market Insights Report 2023 Q3." Available at https://www.seia.org/research-resources/solar-market-insight-report-2023-q3.

US Energy Information Administration (USEIA). 2023a. "Iowa State Energy Profile." Available at https://www.eia.gov/state/print.php?sid=IA.

US Energy Information Administration (USEIA). 2023b. "Levelized Cost of New Generation Resources in the Annual Energy Outlook 2023." Available at https://www.eia.gov/outlooks/aeo/electricity_generation/pdf/AEO2023_LCOE_report.pdf.

Suggested citation

Chen, J., H. Feng E. Hoffman, and L. Seaberg. 2023. "Solar Energy Surge in Iowa: Policies, Public Opinion, and Future Opportunities." Agricultural Policy Review Fall 2023. Center for Agricultural and Rural Development, Iowa State University. Available at: https://agpolicyreview.card.iastate.edu/fall-2023/solar-energy-surge-iowa-policies-public-opinions-and-future-opportunities.■

Agricultural Policy Review is published by the Center for Agricultural and Rural Development. This publication presents summarized results that emphasize the implications of ongoing agricultural policy analysis of the near-term agricultural situation and discussion of agricultural policies currently under consideration. Articles may be reprinted with appropriate attribution. Contact the managing editor at *nmcook@iastate.edu* or call 515-294-3809.

Subscription is free. To sign up, go to *go.iastate.edu/K4ONTN* and submit your information.