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The Economic Value of a Farmer Network: An Application to Pest Management in Iowa

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Abstract

Climate change can lead to increased pest migration and more frequent outbreaks by altering pest life cycles and habitats. Farmers facing increased temperatures or rainfall resort to more pesticides, emphasizing the need for adaptive pest management. This article evaluates the economic benefits of farmer networks for pest management by applying an economic model of social learning to a pilot network in Iowa. Our results show significant variation in the network’s effectiveness. We find that networks are particularly valuable for farmers facing high pest infestation risks, offering over $600 per acre in value against the impacts of extreme heat.

Keywords: Farmer networks, Social learning, Pest management, Climate change, Iowa.

JEL Codes: Q12, Q15, Q16, Q54, Q55

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1 Introduction

Climate change is increasingly recognized as a critical driver of pest migration, range expansion, and more frequent outbreaks, primarily by altering their life cycles and habitats (Hall et al. [2002]; Macdonald et al. [2005]; Gutierrez et al. [2008]; Jackson et al. [2011]; Noyes et al. [2009]; Miraglia et al. [2009]). This shift, which tends to favor pests over crops, is attributed to climate-induced changes in the environment (Müller et al. [2010], Roos et al. [2011]). Research indicates that, while insects can thrive in various climates, they tend to appear earlier and become more active in warmer conditions, a phenomenon exacerbated by climate change (Rosenzweig et al. [2001]; Bloomfield et al. [2006] and Jackson et al. [2011]). As a consequence, farmers in regions experiencing notable increases in temperature or precipitation are often compelled to use higher pesticide dosages to protect their crops, highlighting the need for adaptive strategies in agricultural pest management.

Agricultural economists recognize the importance of farmer coordination as a key strategy for efficient pest management. The works of Lazarus and Dixon (1984) and Vreysen et al. (2007) underline the ineffectiveness of isolated farm-level pest control efforts, particularly given the mobility of pests. Research by Singerman et al. (2017) and Lence and Singerman (2023) further supports the need for coordinated action over broader areas to combat mobile insect pests efficiently. Such collective strategies can help reduce the frequent and widespread use of the same pesticides, a significant factor in developing pest resistance. Hurley and Sun (2019) argue for the establishment of farmers’ networks to promote collaborative pest management efforts across the United States, emphasizing the role of social learning in enhancing these efforts as supported by studies like Miranowski (2016) and Feder and Savastano (2006).

Although the benefits of farmer networks for pest management and the spread of agricultural technologies are well acknowledged, the development and expansion of these networks face several obstacles. Technological barriers, particularly telecommunications challenges in rural areas, pose one part of the problem. Privacy concerns related to sharing farm-specific information on crop and pest management also deter participation. Economic questions further add complexity: determining the economic value of network participation, identifying which farmers would gain the most, understanding the investment needed in communications and pest management technology, and assessing whether these investments would yield profitable returns are all crucial considerations that need addressing to facilitate the growth of farmer networks.

In this article, we aim to explore the economic value of participating in networks for pest management. To achieve this, we adapt a social learning economic model to the context of pest management, drawing from foundational works by Foster (1995), Conley and Udry (2010), Udry (2010), Krishnan and Patnam (2014), and BenYishay and Mobarak (2019), with a specific focus on modeling the optimal timing for pesticide application—a critical decision for farmers. Applying pesticides too early can incur unnecessary costs without significant benefits to production and...
profitability, while late applications can drastically reduce crop yields. Building on this framework, we conduct Monte Carlo simulations of the social learning model to evaluate the economic value of the network under standard climate conditions and assess its adaptation value in scenarios of extreme heat resulting from climate change.

Our simulations center on a pilot farmer network in Iowa (SIRAC), consisting of 121 Iowa Soybean Association (ISA) farmers. This network was established to evaluate new technological advancements in pest management and telecommunications, providing a practical setting to assess the potential benefits and challenges of integrating these innovations in a real-world agricultural context. In our simulations, we distinguish between the contributions of three distinct learning channels: the impact of previous experience in pest management or guidance from external sources, the practical knowledge gained through direct observation or “learning by doing” via scouting technologies, and social learning facilitated by the exchange of information with peer farmers within the network. This approach enables us to evaluate the network’s value across various scouting technologies and degrees of farmer experience.

We have three main results from our simulations of the farmer network.

First, our analysis indicates that the economic benefits of joining a farmer network like SIRAC vary widely under normal climate conditions, ranging from minimal gains to substantial increases in profit per acre. Farms with advanced scouting technologies and less vulnerability to pests—often due to geographical isolation or lower pest pressure—tend to gain the least, while those facing higher risks from environmental factors, market conditions, and possessing less precise scouting methods benefit the most. Specifically, gains vary from as low as $85 to as high as $501 per acre, with the most significant benefits accruing to farmers who are closer to network peers and thus receive more accurate information to manage pest infestations effectively.

Second, we evaluate the economic benefits of expanding the network. Upon expanding the SIRAC network by adding five neighboring farms within a 30-mile radius of each existing farm, thereby increasing the network to 605 farms, we observe the economic benefits of such expansion are modest without implementing targeted signal selection. However, introducing signal selection based on geographic proximity significantly enhances the network’s effectiveness, reducing the average distance for received signals by more than 90%. This targeted approach to signal dissemination leads to notable improvements in the economic benefits of network participation. In the lowest quantile, gains rise to $148 per acre, a 59% increase, while in the highest quantile, gains reach up to $688 per acre, reflecting a 28% enhancement. This demonstrates signal selection’s critical role in maximizing network expansion’s value for farmers.

Third, we explore the network’s adaptation value in scenarios of extreme heat resulting from climate change. We discover that the network offers considerable benefits for farmers most vulnerable to pest infestations, with its value in countering the effects of extreme heat on pest infestations surpassing $900 per acre. Additionally, the network’s potential as an early warning
system for pest infestations could complement agricultural insurance policies, particularly as climate change prompts warmer growing seasons. By alleviating the most severe impacts, the network has the potential to diminish potential losses and, as a result, lower insurance premiums.

This article adds to the expanding body of agricultural and development economics research focused on the value of social learning among farmers. Conley and Udry (2010) demonstrate that farmers rely extensively on insights from their peers. They use an interconnected network of information to assess the comparative profitability of varying fertilizer usage across different weather and soil conditions, finding social learning nearly as impactful as personal experience in agricultural decision-making. Udry (2010) highlights the critical role of social learning in developing extension programs. Further studies by Bandiera and Rasul (2006), Maertens and Barrett (2013), Vasilaky and Leonard (2018), Crane-Drosch (2018), Takahashi et al. (2019), Di Falco et al. (2020), Beaman et al. (2021), and Adjognon et al. (2022) emphasize the influence of social networks on technology adoption, pointing out the significant role of information sharing in enhancing yields.

Despite the sparse literature on social learning in pest management, existing research underscores the necessity of coordinated approaches for effective pest control, highlighting the limitations of isolated farm-level treatments due to pest mobility. Studies by Lazarus and Dixon (1984), Vreysen et al. (2007), Singerman et al. (2017), and Lence and Singerman (2023) stress the importance of broad-scale coordinated treatment to address mobile pest issues, notably reducing the overuse of pesticides and the risk of resistance and Hurley and Sun (2019), underscores the importance of learning from social networks. Our study builds upon these insights by investigating the benefits of learning optimal pesticide timing through farmer networks, a central aspect given the significant impact of timing on pest control efficacy and farm profitability.

Also, in the context of pest management, the role of farmer networks and the sharing of knowledge among peers are increasingly recognized for their potential to reduce uncertainty and encourage the development of innovative, pesticide-free agricultural systems (Wang et al., 2023). Foley et al. (2011) emphasize that a key strategy for achieving "sustainable de-intensification" is minimizing environmentally detrimental inputs. With these resources becoming scarcer, there is a pressing need to enhance production efficiency using equal or fewer resources, highlighting the importance of improved resource use efficiency for global food security.

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1 Additionally, Beaman (2019) show how social connections can affect labor market outcomes, hinting at similar effects in agricultural productivity. Mundia (2004) delves into social learning within diverse populations, highlighting its role in the diffusion of technology during the Indian Green Revolution. Banerjee et al. (2013) explored the spread of microfinance, underlining the importance of social ties in disseminating information and innovation among farmers. BenYishay and Mobarak (2019) illustrate that farmer networks could surpass the efficacy of traditional extension programs at a lower cost. Krishnan and Patnam (2014) find that the effects of social learning, especially concerning the adoption of improved seeds and fertilizers, are more pronounced than learning from extension agents, reinforcing the significance of peer-to-peer learning in agriculture.

2 Other studies, such as Miranowski (2016); Feder and Savastano (2006)

Empirical research indicates that information disparities among farmers can result in either the overuse or underuse of pesticides, with significant implications for both profitability and production efficiency. Studies by Babcock et al. (1992); Antle and Pingali (1994); Carpentier and Weaver (1997); Zhengfei et al. (2006), and Grovermann et al. (2013) highlight how information gaps can lead farmers to overapply pesticides to maximize profits while often disregarding the environmental and health costs. Conversely, a lack of information can also lead to the underuse of...
Dangles (2011) illustrate that farmer-to-farmer learning significantly reduces pest infestations at the community level, suggesting that social learning can lead to sustainable benefits over the long term. This exploration into the value of farmer networks in pest management fills a gap in the current research and provides practical insights into enhancing agricultural practices through improved coordination and social learning.

This article is structured as follows. Section 2 offers background information on the timing of pesticide application and details the SIRAC network. Section 3 outlines the economic model of social learning, adapted specifically for pest management challenges. In Section 4, we detail our simulation design, while Section 5 showcases the results of these simulations. Section 6 concludes and summarizes the policy implications derived from our findings. Appendix A provides in-depth derivations of the economic model of social learning. Appendix B focuses on the most prevalent pests in corn production. Appendix C elaborates on the simulation methodology step by step. Lastly, Appendix D contains supplementary results.

2 Pest Management and Farmer Networks

The Timing of Pesticide Application

In corn production, predominant pest threats include *Diabrotica virgifera* (Western Corn Rootworm), *Diabrotica barberi* (Northern Corn Rootworm), *Helicoverpa zea* (Corn Earworm), *Striacosta albicosta* (Western Bean Cutworm), and *Ostrinia nubilalis* (European Corn Borer, ECB), as elaborated in Appendix B. Despite the distinct phenologies and environmental adaptabilities of these pests, agricultural extension services, such as the Ohio State University Extension, have delineated three principal pest management strategies: the cultivation of transgenic maize varieties expressing Bacillus thuringiensis (Bt) toxins; the application of insecticidal seed treatments; and, the deployment of soil or foliar insecticides.

The recent trend towards preemptive pest management strategies, particularly adopting Bt maize, marks a proactive approach to controlling pests. While Bt maize has significantly reduced pest-related damage, the Bt bacteria are effective against only certain pests, and growing Bt corn requires establishing non-Bt refuge areas to prevent pests from developing resistance. Furthermore, the appearance of Bt-resistant pests in some species highlights the limitations and challenges of current pest management methods, calling for additional suppressive tactics to maintain agricultural productivity. According to the United States Department of Agriculture National Agricultural Statistics Service, pesticide applications were the leading method of pest suppression in U.S. corn production in 2021, as reported by 43% of respondents. Additionally, the most common practice for monitoring was the use of weather data to time pesticide applications, utilized by 60% of respondents [NASS (2014)].

pesticides, as shown by Carrasco-Tauber and Moffitt (1992), Chambers and Lichtenberg (1994), Fernandez-Cornejo et al. (1998), and Lansink and Carpentier (2001), resulting in production inefficiencies and potentially lower yields.
The timing of pesticide application is critical in effective pest management. Delayed application risks escalating pest populations beyond control, while premature treatment may result in ineffectiveness against population growth, necessitating further, costly interventions. Moreover, pinpointing the optimal timing for pesticide deployment is complex, influenced by variables such as climatic conditions and farm management strategies, including crop rotation, field configuration, and seed selection. To navigate these challenges, farmers employ a variety of methods to determine the most effective timing for pesticide use. Predominantly, this involves scouting for pests and utilizing thermal summation techniques, such as growing degree days, to forecast pest population densities and determine the ideal timing for pesticide application.

For example, in their guidance on managing the ECB, Hodgson and Rice (2017) from the Iowa University Extension Services emphasize the ephemeral efficacy of insecticides, underscoring the necessity for timely application. Specifically, they state:

“Insecticides exert their lethality on larvae within a relatively brief window; hence, their application must precede the completion of egg deposition. Postponing treatment risks allowing larvae from initially laid eggs to infiltrate the plant, rendering them impervious to control measures. The precision of application timing emerges as a pivotal factor in the successful mitigation of corn borer infestations via insecticides.”

This guidance highlights the intricate balance required in pest management, particularly the critical importance of synchronizing insecticide application with the pest’s life cycle to maximize efficacy and minimize crop damage.

Examples of pests that can be managed using pesticide applications are Corn Rootworm, Corn Earworm, Western Bean Cutworm, and the ECB. Christian H. Krupke (2017).

The SIRAC Farmer Network in Iowa

Agronomists, engineers, and economists from Iowa State University, Missouri Institute of Technology, the University of Kentucky, and the Iowa Soybean Association (ISA) (reference here) are designing and testing the Smart Integrated Farm Network for Rural Agricultural Communities (SIRAC), which is a connected farm network in Iowa. SIRAC’s goal is to facilitate data sharing, knowledge exchange, and coordinated responses to production threats, contributing to community-led decisions on biological pest spread and mitigation.

Figure illustrates a simulated depiction of the SIRAC network across Iowa, with a total of 121 farms. This simulated network was built using the actual pairwise distance between farms provided by ISA, to protect the confidentiality of each farm’s precise location. Starting from a central reference point in Ames, Iowa, the simulation estimates the spatial positioning of individual farms, utilizing the provided distance metrics. The range of pairwise distances in the dataset is

[SIRAC website: https://sirac.agron.iastate.edu/].
notably broad, starting from less than two feet at its minimum and extending up to approximately 278 miles at its maximum.

Importantly, Figure 1 categorizes the precision of pest detection technologies as either "low" or "high." This classification hinges on the number of traps deployed across the fields, varying from a single trap to a total of seven. Green circles are farms that have installed more than four traps in their fields, categorized under "high" precision, indicating an elevated level of accuracy in pest detection capabilities. On the other hand, red squares are farms with fewer than four traps, indicating a less precise approach to detecting pests.

![SIRAC Network](image1)

![Expanded Network](image2)

Figure 1: Farmers’ Network: Panel (a) displays the SIRAC Network with 121 farmers located in Iowa; Panel (b) shows our hypothetical expanded network with 605 farmers.

To explore the advantages of a broader network, we develop a larger simulation of the farmer’s network, expanding it to include 605 farms. We achieve this expansion by adding five

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6The choice to use four traps as the threshold between the two groups is based on the actual number of traps installed per farm in the SIRAC network, which suggests that farms with more traps can better understand when pests are becoming a problem, allowing them to use pesticides at the right time. This can help prevent pest damage more effectively than farms with fewer traps.
additional neighboring farms at various distances to each farm in the original network. We randomly select these new neighbors within a 30-mile radius, with distances ranging from about 0-27 miles and an average distance of around five miles.

Figure 1 shows this expanded network in Iowa. In this depiction, farms are differentiated by their pest detection capabilities using black squares and purple shapes. Black squares indicate farms that have a basic level of pest detection technology, while purple shapes denote farms with a more advanced or precise system for detecting pests. We base this distinction on the number of traps a farm has installed—we consider farms with more traps as having better quality information about when to treat pests.

By increasing the number of traps, we expect farms to have more accurate data, helping them decide the best time for pest treatment. This expanded network model aims to show how a larger, more connected community of farms can enhance pest management through improved detection and information sharing.

3 A Model of Learning about Pesticide Application

We adapt the farmer learning process concerning pesticide application by extending the target-input model. Development and agricultural economists have widely embraced this economic model, originally developed by Foster (1995) and Jovanovic and Nyarko (1995), due to its simplicity and adaptability in modeling learning across various farming inputs, as highlighted in studies by Beaman et al. (2021), Conley and Christopher (2001), Vasilaky and Leonard (2018), and Ariel BenYishay (2019). Our adaptation of the target-input model focuses on identifying the optimal timing for pesticide application as the key uncertain input requiring farmer education. Essentially, the target-input framework conceptualizes learning as a reduction in the variance associated with production inputs. For instance, a farmer initially inexperienced in pest management might face significant uncertainty in determining the optimal pesticide application timing, reflected in a high variance of estimates. However, as the farmer’s experience and knowledge expand, this variance is expected to diminish, implying an improvement in precision and farmer profitability.

We denote the optimal timing for pesticide application for a given farm $i$ in season $t$ as $\tilde{\tau}_{it}$, which we decompose into two components: (a) the universal optimal timing across farms, represented by $\tau^*$; and, (b) a farm and season-specific term, $\mu_{it}$. We posit that $\mu_{it}$ behaves as an independently and identically distributed (i.i.d.) normal random variable, characterized by a mean of zero and a variance denoted by $\var_\mu^2$. This formulation allows us to capture the commonality in optimal pesticide application timing across different farms and the unique variability each farm and season might introduce.

$$\tilde{\tau}_{it} = \tau^* + \mu_{it} \quad (1)$$

Extension agencies and pesticide suppliers offer guidance on $\tau^*$, the recommended timing for
pesticide application within a specific region. However, $\mu_{it}$, which accounts for farm-specific or within-farm variations due to differences in climate, vegetation, and management practices, can vary significantly. The precise value of $\mu_{it}$ for any given season is not known to the farmer. Instead, farmers typically rely on their personal experience with pest control to make an informed estimate of $\mu_{it}$. To accommodate the inherent uncertainty in estimating $\mu_{it}$, we model it as an i.i.d. normal random variable with a mean of zero and a variance denoted by $\vartheta^2_{it}$. This approach acknowledges the unpredictable nature of agricultural conditions and the adaptive strategies farmers employ in pest management.

**Pest Population:** Farmers determine the optimal time for pesticide application by assessing the pest population on their farms. This process of determining the best application timing is essentially a learning exercise about the pest population dynamics. To this end, we incorporate a straightforward model of pest population growth into the target-input framework, aligning with established pest management research that posits pest populations expand exponentially (add references about pest population growth models). The equation for the pest population $P_t$ at farm $i$, $w$ weeks into the season, is given by:

$$P_t = P_0 e^{r GDD}$$

where $P_0$ represents the initial pest population at the start of the season and $r$ denotes the pest’s internal growth rate. To address the pest population’s uncertainty, we define $P_t$ as a random variable normally distributed with mean $\mu_{P_t}$ and variance $\vartheta^2_{P_t}$. As farmers scout their fields, they accrue more precise information about $\mu_{P_t}$, allowing for an increasingly accurate estimation of future pest populations and, consequently, a reduction in the variance of these estimates throughout the season. To simplify the notation, we exclude the season subscript in subsequent equations.

**Production Function:** At the heart of the target-input model lies a production function, which models the farm’s maximum potential yield and incorporates a loss function. This loss function quantifies yield reductions attributable to deviations from optimal input utilization. Specifically, for pest management, we define the loss function in relation to deviations from the ideal timing of pesticide application:

$$q_i(\tau_i) = \bar{q}_i - \alpha g(GDD)(\tau_i - \bar{\tau}_i)^2$$

where $q_i$ represents the quantity of corn produced per acre on farm $i$, with $\bar{q}_i$ denoting the maximum potential yield. Yield losses occur as a result of deviations from the optimal pesticide application timing, $\bar{\tau}_i$. To streamline the model, we exclude other production inputs such as labor and fertilizer, although their inclusion would not alter the target-input model’s outcomes. The pest growth function $g(GDD)$ is determined by growing degree days (GDD), reflecting temperature’s role in pest development. We expect yield losses to escalate as the season progresses, correlating
with increased pest density in the field. The parameter $\alpha$ serves as a scaling factor that measures the impact of timing deviations on corn production sensitivity.

The quadratic formulation of the production function serves as an approximation for the loss function surrounding the optimal timing of pesticide application. This symmetrical loss structure around the optimum reflects the potential for yield reductions due to premature applications and losses stemming from infestations caused by delayed applications. As deviations from the optimal timing expand, we expect the yield losses associated with significantly late applications to escalate. This quadratic approach is critical within the target-input model framework, as it facilitates the analysis of farmer profitability in relation to the variances of input levels.

**Farmer Profitability:** To understand how variances in the timing of pesticide application influence a farmer’s expected profits, we analyze the farmer profit maximization problem. A farmer, denoted as $i$, selects the timing of pesticide application, $\tilde{\tau}_i$, and the number of scouting trips, $S$, aiming to maximize her expected profits $E(\pi_i)$:

$$E(\pi_i) = \max_{\tau_i, s} p q_i(\tau_i) - s_i \times a_i \times r - c_i$$

where $p$ represents the price of corn; $r$ is the average scouting cost per acre; $a_i$ denotes the total acreage scouted; and $c_i$ captures the total cost of fertilizer application. Maximization of the farmer’s expected profit implies that $\tau_i = E(\tilde{\tau}_i) = \tau^*$, suggesting the farmer will opt for the average optimal timing. The optimized profit function then becomes:

$$E(\pi_i^*) = p \bar{q}_i - \alpha g(GDD) (d^2_{\tilde{\tau}_i} + d^2_{\mu}) - s_i \times a_i \times r - c_i$$

This equation links expected profitability directly to two types of variance. The first, $d^2_{\tilde{\tau}_i}$, captures the uncertainty around the optimal timing of pesticide application, which farmers can reduce through learning from their own past experience and through their interactions within their social network. The second, $d^2_{\mu}$, represents uncontrollable random effects, like specific weather events or unique pest developments, that learning processes cannot mitigate. Equation 5 is a central result of the target-input model, connecting the learning mechanisms directly to farmer profitability. Using Bayes’ rule for a normal distribution allows for the derivation of a straightforward equation for the variance of the uncertain input choice, $d^2_{\tilde{\tau}_i}$, highlighting the impact of both experiential learning and social learning on decision-making processes.

**Learning by Doing:** Farmers gain insights from their own experiences. We divide the growing season into weeks, starting with the farmer’s initial estimate of pest population growth based on prior experience, weather forecasts, and chosen management practices. As the season progresses, the farmer can update her pest population estimates weekly through scouting.

By applying Bayesian updating to the population growth process, we derive an expression for $d^2_{\tilde{\tau}_i}$ that incorporates learning by doing. We use the relationship between the optimal tim-
ing of pesticide application and the pest population to derive the variance \( \vartheta_{\tau_i}^2 \), conditional on an observation of the population \( P_w \) in week \( w \). Through Bayesian rule, we find:

\[
\vartheta_{\tau_i}^2 = \frac{1}{\rho_0 + \gamma \times \rho_S}
\]

(6)

where \( \rho_0 \) represents the precision of the initial estimate of optimal pesticide application timing at the season’s start. Precision, the inverse of variance (\( \rho_0 = \frac{1}{\vartheta_0^2} \)), improves with more accurate initial estimates. For instance, experienced farmers are likely to have more accurate application timing estimates, leading to lower \( \vartheta_0^2 \) and higher \( \rho_0 \), thus reducing \( \vartheta_{\tau_i}^2 \) and enhancing profitability as shown in equation 5.

The second term, \( \rho_S \), reflects the precision of the farmer’s learning technology, such as the accuracy of information obtained from scouting, inversely related to its variance (\( \vartheta_S^2 \)). High-quality scouting increases \( \rho_S \). Investment in technologies like cameras and trapping devices can also increase the precision \( \rho_S \). Finally, the precision of the learning technology is multiplied by a factor \( \gamma \) in equation 6 that adjusts for pest population growth characteristics and scouting frequency, influenced by factors such as pest growth and death rates, the number of scouting reports, and the correlation between pest population and optimal pesticide timing. Appendix A derives \( \gamma \), which increases with more frequent scouting, illustrating a balance between scouting frequency and technology quality. Farmers with less precise technology may need more frequent scouting to achieve the profitability levels of those with advanced technology.

**Learning from Others (Social Learning):** Farmers also benefit from the knowledge and experiences of their peers within their social networks. For instance, a farmer equipped with advanced pest detection technology might share valuable insights about unusual pest developments with neighboring farmers, enhancing the network’s collective understanding of pest management. This exchange of information, or ‘signals’, particularly regarding the optimal timing for pesticide application, forms a critical component of social learning in pest management. Specifically, in the pest management application, we define a signal as a neighboring farmer’s estimate of their optimal time of pesticide application. A farmer might receive \( N \) signals from peers each season, with the quality of these signals varying significantly.

In the target-input model, precision quantifies the informational value of a signal, \( \rho_N \), defined as the inverse of the variance of the optimal timing of pesticide application from the signal’s sender, \( \rho_N = \frac{1}{\vartheta_\xi^2 + \vartheta_\tau_j^2} \), where \( \xi \) represents an additional error term to account for the signal’s noise. While we initially assume signal precision from peer farmers is uniform for simplicity, our simulations introduce variability in signal precision based on the geographic proximity among farmers, aligning with methodologies commonly employed in learning literature [Conley 2001].

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7Appendix A details the derivation, resulting in the optimal timing’s variance conditioned on \( P_w \) as \( \tilde{\tau}_{\mid |P_w} \sim N(\tau^\star, \vartheta_\tau^2(1-\rho_{\tau,p})) \), where \( \rho_{\tau,p} \) denotes the correlation between the optimal application timing \( \tilde{\tau} \) and pest population \( P_w \).

8We derive in Appendix A an equation for \( \gamma \) using the Bayes rule. \( \gamma = \left[ \frac{\rho_{\tau[p]}^2}{\rho_0 + \gamma \times \rho_S} \right] \). \( \gamma \) is always positive given that the correlation between pest population and the timing of optimal pesticide application, \( \rho_{\tau[p]}^2 \), is positive.
As part of a network, receiving $N$ signals allows a farmer to refine her estimates for the optimal pesticide application timing on her farm. For example, learning about a peer’s observation of unexpected pest population growth could prompt a farmer to adjust her own estimates accordingly. Through Bayesian updating, we derive a revised equation for $\vartheta_i^2$ that incorporates social learning:

$$\vartheta_i^2 = \frac{1}{\rho_0 + \gamma \times \rho_S + N \times \rho_N}$$

This equation extends equation 6 by adding a third term, $N \times \rho_N$, to the denominator, reflecting the impact of social learning. The effectiveness of learning increases with the receipt of a greater number of high-precision signals ($N$), and with precise signals from the network, high $\rho_N$. This improvement in learning reduces the variance $\vartheta_i^2$, subsequently boosting farmer profits. Moreover, the product $N \times \rho_N$ suggests a trade-off between the quantity and quality of signals, indicating that receiving numerous high-quality signals can significantly enhance a farmer’s understanding and management of pest populations.

The Value of Social Learning for Pest Management: The value of social learning in pest management is quantified by the additional expected profit a farmer gains by integrating information from peers into her decision-making process regarding the uncertain timing of pesticide application. The profit function in equation 5 defines this concept, which translates the impact of learning into monetary terms. As learning progresses, the variance $\vartheta_i^2$ diminishes, leading to an increase in expected profit. Therefore, the value of social learning is represented by the difference in expected profits—with and without the influence of peer learning, as detailed in equation 7. To quantify this value, $\Delta$, we calculate the difference between the expected profit function incorporating social learning (via equation 7) and the expected profit absent social learning (via equation 6):

$$\Delta = E(\pi^*_i | \text{with social learning}) - E(\pi^*_i | \text{without social learning})$$

$$\Delta = -\alpha g(GDD) \left[ \frac{1}{\rho_0 + \gamma \times \rho_S + N \times \rho_N} - \frac{1}{\rho_0 + \gamma \times \rho_S} \right]$$

We use equation 8 to simulate the value of social learning pest management within a network of farmers in Iowa. Naturally, farmers can learn more from their peers than about optimizing pesticide application. Thus, our simulated values for social learning will underestimate the total value of learning within the network. However, we can extend the framework to other applications with alternative farming inputs such as fertilizer and labor. The value of learning will be higher,
the larger the uncertainty about the optimal use of an input or the optimal choice of management practice. The application to pest management is important because of the uncertainty about the key choice of the time of pesticide application. Furthermore, we can extend the framework for the more general case of multiple pests.

4 Methods: Monte Carlo Simulations

To evaluate the economic value of a network of farmers engaged in pest management, this study employs Monte Carlo simulations to project the expected profits of farmers, with and without the effects of social learning. These simulations involve generating thousands of random parameter samples from the economic model for the network’s value (as in equation 8). These samples are the basis for calculating the expected gain and the distribution of economic gains attributable to the farmer network.

In each simulation, we estimate the farmer’s expected gain under three distinct scenarios that represent different learning mechanisms: previous knowledge; scouting (learning by doing); and, social learning. The initial scenario, termed the baseline model, assumes farmers have no access to external information to determine the optimal timing for pest control, relying instead on their knowledge and previous experiences. As a result, in this scenario, farmers’ expected losses are the highest due to a discrepancy between their chosen timing for pest management and the ideal, most effective timing. Next, we assess the impact of learning through scouting, which involves direct experience in the field. Finally, we explore the benefits of incorporating social learning within the farmer network. With each addition of new learning channels, we calculate the decrease in losses attributed to pest infestations.

The simulation of the distribution of a farmer’s expected gain involves drawing a sample of 10,000 observations from the distribution of the model parameters. Our model is based on two primary sets of parameters, summarized in table 1. The first includes endogenous parameters, which are influenced by the farmer’s decisions. These include the frequency of scouting activities, which reflect a farmer’s effort to monitor pest infestation levels. For the purpose of our simulations, we assume that farmers conduct scouting weekly throughout the farming season. Another key endogenous parameter is the farmer’s initial estimate regarding the optimal timing for pesticide application. We categorize initial knowledge into two levels: low initial precision, representing farmers with limited experience and knowledge about the optimal timing for pest treatment; and, high initial precision, indicative of farmers with extensive experience. In our simulations, due to the absence of specific data regarding farmers’ knowledge and experience, we make the assumption that all farmers within the network possess limited knowledge and experience. This assumption does not impact the calculation of the network value because we difference out the value of initial experience.

The simulation also incorporates two additional endogenous parameters: the precision of the pest detection technology; and, the precision of the informational signal from the farmer net-
Table 1: Simulation Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of farmers- SIRAC network</td>
<td>121</td>
</tr>
<tr>
<td>Number of farmers- expanded network</td>
<td>605</td>
</tr>
<tr>
<td>Initial precision of farmer’s estimate</td>
<td>Uniform(0, 1)</td>
</tr>
<tr>
<td>Precision of the scouting</td>
<td>Number of traps / Maximum number of traps</td>
</tr>
<tr>
<td>Precision of the signals</td>
<td>$\frac{1}{10} \sum_{i=1}^{10} signal_i \times w_i$</td>
</tr>
<tr>
<td>Distance from signal sender:</td>
<td></td>
</tr>
<tr>
<td>0 to 10 miles</td>
<td>1.00</td>
</tr>
<tr>
<td>10 to 25 miles</td>
<td>0.75</td>
</tr>
<tr>
<td>25 to 50 miles</td>
<td>0.50</td>
</tr>
<tr>
<td>More than 50 miles</td>
<td>0.25</td>
</tr>
<tr>
<td>Pest growth rate ($g$)</td>
<td>determined by $\frac{dP}{dt} = rP(1 - \frac{P}{\kappa})$</td>
</tr>
<tr>
<td>Pest death rate ($\delta$)</td>
<td>Uniform(0, 0.4)</td>
</tr>
<tr>
<td>Pest carrying capacity ($\kappa$)</td>
<td>$N(22, 0.5)$</td>
</tr>
<tr>
<td>Pest intrinsic growth rate ($r$)</td>
<td>$1 + g - \delta$</td>
</tr>
<tr>
<td>Pest initial population ($P_0$)</td>
<td>$N(2, 0.5)$</td>
</tr>
<tr>
<td>Corn Price</td>
<td>$N(6.4, 0.83)$</td>
</tr>
<tr>
<td>Corn yield</td>
<td>$N(173, 5)$</td>
</tr>
<tr>
<td>Frequency of scouting</td>
<td>10 per season</td>
</tr>
<tr>
<td>Quantity of the received signals</td>
<td>10</td>
</tr>
<tr>
<td>Growing Degree days (GDD)</td>
<td>$N(1500, 500)$</td>
</tr>
<tr>
<td>Number of simulations</td>
<td>10,000</td>
</tr>
</tbody>
</table>

Note: We generated 10,000 observations with replacement for the parameters following a normal distribution. The precision of the signals was assessed based on the quantity of traps at the sources of these signals. To incorporate the aspect of trust that farmers attribute to these signals, we allocated weights based on the spatial distances between the signal origins and the recipients.

We quantify the accuracy of the pest detection technology based on the number of traps a farmer installs in their field, which we calculate by dividing the number of traps placed in a given field by the maximum number of traps used, which is seven. Consequently, the precision parameter for the technology varies from 0.14 to 1. A precision value of 0.14 indicates a field with just one trap installed, suggesting minimal technology deployment. Conversely, a precision value of 1 denotes the installation of seven traps, the maximum considered in our study, indicating the highest level of technological deployment for pest detection. In our simulations, we categorize scouting precision as low or high. Low precision scouting corresponds to the average precision for farms with trap counts at or below the network’s median (four traps). We determine high-precision scouting by the average precision of farms with trap counts above the network’s median.

To quantify the precision of the informational signal received from the farmer network, we employ a proxy combining two elements: the count of traps installed in the originating field; and, the spatial distance between the signal senders and the recipient. The number of traps installed measures the information accuracy shared by the senders, with a lower count indicating reduced precision. Additionally, we compute a weighted average for the signal’s precision as received by a farmer, where the distances from the senders to the receiver determine the weights. For each
farm, we cluster the neighbors based on distance and assign weights for each group of neighbors.

In our simulations, we account for the distance between signal origins and destinations by assigning weights to capture a farmer’s trust in the signal’s relevance. Each farmer receives ten signals, with the weight of each signal determined by the distance from its source. Specifically, we weight signals originating from within a 10-mile radius at 1, acknowledging the strong potential for social ties or trust among nearby farmers. We assign signals from 10 to 25 miles away a weight of 0.75, those from 25 to 50 miles receive a weight of 0.50, and we give signals from sources over 50 miles away a weight of 0.25. This system reflects the understanding that farmers are more likely to observe and trust their close neighbors’ farming decisions and outcomes. Our simulations assume that each farmer receives ten signals. We compute the weighted average of the ten signals for each signal-receiving farmer using the assigned weights. High precision refers to the average of signals with precision greater than the median value for all signal receivers. Conversely, low precision signal refers to the average of signals with precision less than the median value.

The second set of parameters are exogenous factors, which are external to the farmer’s control and stem from the broader environmental context. A key exogenous parameter is the growth and death rate of the pest or insect population, as it directly affects the population size and dynamics of the pests over time. The growth and mortality rates among the pests are contingent upon various factors, one of which is the total GDDs accumulated during each season. GDDs are a measure of heat accumulation over time and serve as an important gauge for understanding the development and reproductive cycles of the pest population. Additionally, the carrying capacity for pests, indicating the highest pest population that the agricultural ecosystem can sustain, is another important exogenous parameter. Multiple ecological variables, such as the availability of host plants, the presence of natural predators, and the general environmental conditions shape this capacity. In our simulations, we derive the pest-related parameters from historical data concerning the ECB, as Appendix B details. For instance, we assume the initial distribution of larvae follows a normal distribution with an average of two larvae per plant, reflecting ECB statistical data. Table 4 in Appendix B documents the economic impact of the larvae, providing a detailed reference for the loss estimations related to ECB infestations.

Additional exogenous parameters include corn prices and the average corn yield, significantly impacting farmers’ input decisions and profitability. We assume that the price of corn and the average yield are normally distributed around their historical averages, specifically $6.40 per bushel for the price and 173 bushels per acre for yields. These averages serve as the basis for our simulations, reflecting the inherent uncertainties associated with corn production. To accommodate the variability in price and yield, we generate a sample of 10,000 observations from these normal distributions, thereby incorporating the uncertainties related to price and yield into our analysis.

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11The median value for the SIRAC network is 1.88, the average for high precision is 5.04 (sd= 2.34), and the average for low precision signal is 0.95 (sd= 0.45). The Tables D.1, D.2, and D.3 in Appendix D offer descriptive statistics for the calculated signal precision for our different simulation models.

12We calculated the average corn price using the corn price data for the last two decades sourced from Iowa State Extension: https://www.extension.iastate.edu/agdm/crops/pdf/a2-11.pdf.

1320-year average yield calculated based on the corn yield data from USDA - NASS.
5 Simulation Results

5.1 Baseline Scenario

Our simulations begin with a baseline scenario, establishing a reference point for comparing the outcomes from simulations that include the SIRAC network. This baseline scenario is based on four simplifying assumptions, which we later relax in subsequent sections. First, we assume that farmers within the network have limited knowledge and experience regarding the optimal timing for pest treatment. This acknowledges the challenges farmers may face in making informed pest management decisions. Second, we categorize the precision of scouting technology into two levels: low and high precision. Third, we assume that farmers in the network receive ten uniform informative signals from their peers. Additionally, we define two precision levels for the network signal: low and high. In this baseline scenario, we treat the precision of the farmer’s scouting and network signals as following a standard normal distribution. We calculate low and high precision values as the averages of signal precision below and above the median. This model does not consider the geographical distance between signal senders and receivers, implying an equal level of trust in all signals, regardless of their source. Lastly, we assume that the pest carrying capacity has a normal distribution with an average of 3 per plant and a standard deviation of 0.5. This approach provides a simplified framework for assessing the network’s impact, which we expand upon in the subsequent analyses.

Figure 2 illustrates the simulation results using the baseline model. The blue histograms across each graph display the distribution of expected gains for farmers who utilize scouting to gather insights on the pest population, compared to a baseline where decisions are made solely based on prior knowledge. Meanwhile, The orange histograms show the expected gains for farmers who improved their decision-making with scouting and information obtained through their network, enhancing their pest management strategies.

Each subgraph within Figure 2 corresponds to a distinct scenario regarding the precision of information derived from scouting and the network. For example, Figure 2a illustrates outcomes for a scenario where both scouting and network-derived learning signals have low precision. This scenario reflects a context in which the scouting technology is relatively undeveloped, and the reliability of information from the network is uncertain. Conversely, Figure 2d showcases the case where the precision from both scouting and networking is high, indicating advanced scouting technology and reliable network information. These distinctions show how varying information precision levels can impact pest management strategies’ effectiveness.

Within our model, farmers can learn through three methods: their own previous experience; direct observation and action (scouting); and, exchanging information within a network. Adding each new learning method improves how effectively farmers can manage pests, reducing their potential losses. A reduction in losses due to better pest management when farmers use scouting methods in their fields represents the benefit gained from scouting alone, shown by the blue histogram. Similarly, the further decrease in losses when employing both methods measures the advantage of combining scouting with networking, depicted by the orange histogram. Therefore,

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14 We fix the precision of the farmer’s initial knowledge at 0.14, which is the average value for the sample of farms with precision lower than the median from a uniform distribution. The fixed value for the previous knowledge precision does not affect simulation results because it is constant across simulations for scouting and for scouting and networking.

15 The assumption is based on the statistics provided by Christian H. Krupke (2017). We revise this assumption for the simulations for SIRAC and expanded network based on the values suggested in Case et al. (2002) and Tyutyunov et al. (2008).
the difference between the gains shown in the orange and blue histograms highlights the extra value provided by the social network. This differential quantifies the network’s contribution beyond what scouting alone can offer, underlining the significance of collaborative learning in enhancing agricultural practices.  

![Figure 2: Simulation of Farmer’s Expected Gains by Signal Precision - Baseline Model](image)

Note: Figure 2 shows the distribution of farmer’s expected gain from learning from scouting and from the network. Farmers have three channels of learning: previous knowledge, scouting, and network. The blue histograms plot the distribution of farmer’s gain from scouting relative to the reference case of only previous knowledge. The orange histograms plot the distribution of farmer’s gain from scouting and networking relative to the case of only previous knowledge. The difference between the orange and blue histograms captures the gain from the network. The dashed vertical line represents the median value of each distribution. Each graph plots distributions for different precision levels of the signals from scouting and from the network.

The baseline model serves as a foundation for comparing scenarios where we take the network’s influence into account. According to our simulations, the average expected gain from scouting activities, when utilizing low precision technology, stands at approximately $15 per acre. However, the range of potential reduction in losses due to scouting varies widely, from as little as $0 to as much as $100 per acre, depending on the farm’s specific circumstances (as Figures 2a and 2b illustrate). The lower end of this range corresponds to conditions where a farm experiences no pest infestation, in which case the value of scouting for gathering information is negligible. On the other hand, farms facing severe pest challenges realize the greatest advantage from scouting efforts. Enhancing the precision of scouting technology raises the average expected benefit from scouting activities to $60 per acre. In instances of high vulnerability to pest attacks, the benefit can surge to over $200 per acre (Figures 2c and 2d).

The introduction of access to a network of farmers, adding a third channel of learning, notably alters the distribution of expected gains for farmers. Initially focusing on scenarios where scouting technology has low precision, our simulations reveal that the expected gain from inte-

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16Our simulation of network gains does not need the specification of a cost for scouting, as any such cost would cancel out in the computation of the farmer’s expected gains from the network, being incorporated in the orange and blue histograms.
grating scouting with network learning varies significantly. With network signals of low precision, the expected gain begins at $35 per acre (as seen in Figure 2a), and increases to $70 per acre when the network signals are of high precision (illustrated in Figure 2b). The maximum potential gain exceeds $100 per acre with low precision signals and can surpass $200 per acre with high precision signals. Transitioning to scenarios where scouting technology is highly precise, the distribution of expected gains slightly shifts right (as Figures 2a and 2b depict). This observation suggests that while a uniform improvement in scouting technology benefits all farms, farmers also having the capability to learn from their peers somewhat limits the marginal gain of such improvement.

The difference between the expected gain from utilizing both scouting and network learning (indicated by a vertical orange dashed line) and the expected gain from solely relying on scouting (marked by a vertical blue dashed line) quantifies the economic value derived from learning within a farmer network, as depicted in Figure 2. This differential, representing the network’s value, is notably higher, approximately $50 per acre, when the precision of the scouting signal is low, yet the precision of the network signal is high, as illustrated in Figure 2b. Conversely, in situations where the scouting signal’s precision is high and the network signal’s is low, the incremental benefit of incorporating the farmer network into pest management strategies is minimal, as shown in Figure 2c. However, the learning value derived from the network increases significantly at the distribution’s tail, particularly for farmers who are most at risk from pest infestations. For these vulnerable farmers, the value attributed to the network can surpass $200 per acre.

5.2 Simulation of the SIRAC Network and ECB Pest Management

In this section, we extend our simulation to assess the economic value of a network in a more realistic setting for pest management. We use the actual number of traps installed across 121 farms within the SIRAC network, along with the pairwise distances among these farms, to determine the precision of scouting and the precision of network signals. Initially, we assign a unique precision level for the scouting technology to each farm, based on the real number of traps installed. We calculate the precision for each farm’s scouting as the ratio of the number of traps to the maximum observed, which is seven.

Next, we account for variations in the precision of signals received by farmers from their network peers. This adjustment considers both the scouting precision of the sending farm and the geographical distance to the receiving farm. In line with the baseline model, each farmer receives 10 signals from within the network, but now, each signal varies in precision. We use a weighted average, where the distance from the sender to the receiver gives the weight, to determine the precision of a signal received by a farmer. Specifically, a signal from a nearby farm equipped with high-precision scouting technology will carry more weight than one from a distant farm with low scouting precision. This approach allows us to investigate how both technological and spatial factors influence the value of information exchanged within the network.

Our SIRAC simulations focus on pest management strategies targeting the ECB, primarily because the ECB’s life cycle aligns well with the pest population dynamics outlined in equation 2. Our model is adaptable and can be extended to other pests by modifying the population growth function to fit specific pest life cycles.

Table 1 presents all the parameters used in our simulations, including their values and dis-
tributions. We tailor these parameters—specifically the pest death rate, carrying capacity, and initial population to the ECB based on empirical data and research findings detailed in the cited study. Notably, we adjust the average pest carrying capacity between the baseline scenario and the SIRAC simulation—while we set it to 3 in the baseline to simplify initial assessments, we revise it to 22 in the SIRAC simulation to more accurately reflect the ECB’s ecological reality and potential for population growth under optimal conditions. We model the growth rate of the ECB pest population as a function of GDDs, since its population growth is contingent on the accumulation of degree-days above the ECB’s developmental threshold temperature of 50°F.

Figure 3 displays the expected gains for farmers in the SIRAC simulation, with the blue and orange distributions indicating the farmer’s gains with scouting (blue) and with scouting plus networking (orange) for varying precision levels of scouting and network signals, consistent with the baseline model. The overall trends between the baseline and SIRAC simulations remain similar, highlighting the significant benefits of network participation. Particularly, the difference in expected gains between the orange (network plus scouting) and blue (scouting only) distributions, marked by vertical dashed lines, is notably larger in scenarios where the precision of scouting technology is lower (as comparisons between figures 3b and c illustrates).

(a) Scout precision: Low; Network precision: Low
(b) Scout precision: Low; Network precision: High
(c) Scout precision: High; Network precision: Low
(d) Scout precision: High; Network precision: High

**Figure 3: Simulation of Farmer’s Expected Gains by Signal Precision - SIRAC Network**

Note: Figure 3 shows the distribution of farmer’s expected gain from learning from scouting and from the network for the SIRAC network with an application to management of ECB pest. Farmers have three channels of learning: previous knowledge, scouting, and network. The blue histograms plot the distribution of farmer’s gain from scouting relative to the reference case of only previous knowledge. The orange histograms plot the distribution of farmer’s gain from scouting and networking relative to the case of only previous knowledge. The difference between the orange and blue histograms captures the gain from the network. The dashed vertical line represents the median value of each distribution. Each graph plots distributions for different precision levels of the signals from scouting and from the network.

However, two differences emerge between the results of the baseline and SIRAC models. First, the magnitude of gains from network participation is considerably higher in the SIRAC model. Specifically, with low precision scouting technology, expected gains from network participation rise to $70 per acre with low precision network signals (Figure 3a) and to $231 per
acre with high precision network signals (Figure 3b). With high precision scouting technology, the benefits from network participation decrease but remain significant, at $20 and $80 for low and high precision network signals, respectively. The primary reason for this increased network value in the SIRAC simulation is the higher pest carrying capacity, adjusted from 3 to 23. This adjustment suggests a greater likelihood of severe pest infestations, potentially leading to more substantial yield losses. Consequently, as the potential severity of pest threats escalates, the value of the network as a learning channel increases.

The second notable distinction in the simulation results for the SIRAC network lies in the widened spread of the distribution of gains from network participation. We attribute this increased variability among farmers’ gains to the significant heterogeneity in the precision of scouting and network signals. Farmers equipped with advanced scouting technologies tend to benefit less from the network, as their existing systems already provide them with a high level of pest management efficiency. Conversely, farmers that have less sophisticated scouting technology but have access to more precise signals—potentially due to their proximity to experienced farmers—stand to gain more from network participation. This variation in gains underscores the impact of spatial and technological factors on the value derived from the network. Understanding these dynamics offers valuable insights for optimizing network design.

The Distribution of Network Gains

To identify which farms benefit most from network participation, we analyze the expected gains from network involvement across different quantiles of the distribution of gains. Table 2 provides a detailed look at the economic gains farmers can anticipate from being part of the network, segmented by quantiles. This analysis combines the results of all scenarios illustrated in the four graphs of Figure 3. Furthermore, Table 2 includes farm characteristics at each percentile of the distribution of gains. The characteristics examined include the average pairwise distance between farms within each percentile, the average number of GDDs, the precision levels of scouting and network signals, and data on corn prices and yields. These attributes help identify the factors contributing to the differential benefits observed across the network.

We observe the smallest expected gain from participation in the SIRAC network at the 5th quantile, amounting to $85 per acre (Panel A of Table 2). A greater average distance from their peers within the network, the lowest accumulation of GDDs, and receiving the least precise network signals characterize farms that benefit the least from the network. Additionally, these farms have the most advanced scouting technology available to them and the lowest average corn prices and yields. Such farms are initially less susceptible to pest infestations and possess a superior capability to gather and learn from their own scouting data. Moreover, the information they receive about pest management from their peers through the network tends to be less accurate, further diminishing the relative value of network participation for these particular farmers.

The highest gain from participation in the SIRAC network reaches $501 per acre at the 95th quantile. Farmers in this high quantile are more vulnerable to pest infestations due to a greater accumulation of GDDs, and they benefit from the highest corn prices and yields. Consequently, these farms have more at risk in the face of ineffective pest management. Additionally, lower precision in their scouting efforts characterizes farmers at the 95th quantile. However, they receive the most precise signals from the network, partly due to their proximity to other members of the network. Therefore, the farmers who benefit the most from the network are most at risk due to external environmental and market conditions, and are also less capable of independently acquiring optimal pest management knowledge.
Table 2: The Farmer’s Expected Gain from Network Participation

<table>
<thead>
<tr>
<th></th>
<th>Expected Gain from Network $ per acre (St.Dev)</th>
<th>Sender–Receiver Distance (miles)</th>
<th>GDD</th>
<th>Signal Precision Network Avg.</th>
<th>Scouting Avg. P90</th>
<th>Corn Price ($ per bushel)</th>
<th>Corn Yield (bushels per acre)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
</tr>
<tr>
<td>A. SIRAC Network</td>
<td>Q5 85 (17)</td>
<td>119</td>
<td>28.04</td>
<td>1,816</td>
<td>2176</td>
<td>0.21</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>Q25 149 (22)</td>
<td>116</td>
<td>25.97</td>
<td>1,847</td>
<td>2226</td>
<td>0.28</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>Q50 231 (26)</td>
<td>112</td>
<td>19.74</td>
<td>1,868</td>
<td>2266</td>
<td>0.22</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>Q75 325 (30)</td>
<td>110</td>
<td>16.37</td>
<td>1,888</td>
<td>2300</td>
<td>0.48</td>
<td>0.68</td>
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<tr>
<td></td>
<td>Q95 501 (114)</td>
<td>109</td>
<td>14.79</td>
<td>2,004</td>
<td>2460</td>
<td>0.51</td>
<td>0.68</td>
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<tr>
<td></td>
<td>B. Expanded Network</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Q5 93 (19)</td>
<td>116.20</td>
<td>37.00</td>
<td>1,802</td>
<td>2155</td>
<td>0.26</td>
<td>0.21</td>
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<tr>
<td></td>
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<td>110.60</td>
<td>32.00</td>
<td>1,847</td>
<td>2230</td>
<td>0.34</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>Q50 252 (28)</td>
<td>103.80</td>
<td>29.00</td>
<td>1,865</td>
<td>2260</td>
<td>0.56</td>
<td>1.00</td>
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<tr>
<td></td>
<td>Q75 353 (32)</td>
<td>96.93</td>
<td>29.85</td>
<td>1,891</td>
<td>2322</td>
<td>0.69</td>
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<td></td>
<td>Q95 539 (117)</td>
<td>93.21</td>
<td>29.35</td>
<td>2,007</td>
<td>2459</td>
<td>0.75</td>
<td>1.00</td>
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<td></td>
<td>C. Expanded Network with Signal Selection</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
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<td></td>
<td>Q5 148 (30)</td>
<td>7.04</td>
<td>2.23</td>
<td>1,809</td>
<td>2164</td>
<td>0.96</td>
<td>1.00</td>
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<tr>
<td></td>
<td>Q25 247 (31)</td>
<td>6.93</td>
<td>2.23</td>
<td>1,821</td>
<td>2198</td>
<td>0.96</td>
<td>1.00</td>
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<tr>
<td></td>
<td>Q50 347 (30)</td>
<td>6.83</td>
<td>2.23</td>
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<td>2237</td>
<td>0.97</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>Q75 461 (38)</td>
<td>6.76</td>
<td>2.23</td>
<td>1,898</td>
<td>2313</td>
<td>0.97</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>Q95 688 (109)</td>
<td>6.69</td>
<td>2.20</td>
<td>2,030</td>
<td>2501</td>
<td>0.97</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Panel A summarizes the farmer’s expected gains from participating in the SIRAC network for ECB pest management. Panel B reports gains for the expanded network. Panel C reports gains for the expanded network with signal selection. The table reports averages, standard deviations and tail values at the 10th percentile (P10) and the 90th percentile (P90).
Network Expansion

To evaluate the benefits of expanding the SIRAC network, we simulate an enhanced version of it. In this version, we introduce five additional neighboring farms within a 30-miles radius for each of the 121 existing farms in the SIRAC network, resulting in a total of 605 farms. Additionally, we randomly assign a varying number of traps to each of the newly added farms. The simulation parameters remain consistent with those used in the previous SIRAC simulation. Figure 1 presents a map illustrating this expanded network in Iowa.

Table 2, Panel B, shows the outcomes of the simulation for the expanded network, focusing on five quantiles in the distribution of farmers’ gains from participating in the network. As anticipated, the simulation reveals that the expanded network brings farmers geographically closer to each other across all quantiles, as indicated by the reduced pairwise distance (Column 2). This proximity enhances the precision of the information signal within the expanded network (Column 6). A notable benefit of this larger network is the increased accessibility to peer farmers situated closer by.

The simulation of the expanded network reveals a uniform 9% increase in farmers’ expected gains across all quantiles, underscoring the positive impact of enhanced signal precision in a larger network (Table 2 Panel B, Column 2). This improvement in gains reflects the enhanced quality of signals concerning pest infestations, derived from closer neighbors. Such proximity enables farmers to fine-tune their pest management strategies more effectively. However, the benefit observed from expanding the network to five times its original size is smaller than expected. The key issue lies in the random selection of network signals—despite an increase in the number of peer farmers, some of whom are now closer, the process does not prioritize signals based on the geographical proximity between sender and receiver. Consequently, farmers may still receive signals from peers several hundred miles away. Without a refined approach to selecting signals, the modest gains from network expansion are primarily due to a slightly higher chance of receiving a more accurate signal. To address this limitation, we next simulate the expanded network incorporating a mechanism for selective signal reception.

Expanded Network with Signal Selection

In this section, we assess the advantages of network expansion coupled with signal selection. Unlike the previous setup, farmers now exclusively receive signals from the 10 nearest peer farmers, ensuring that the information is geographically relevant. All other simulation parameters remain consistent with the earlier simulation. Panel C of Table 2 presents the results of this refined simulation approach. This adjustment aims to enhance the precision and applicability of the information exchanged within the network, potentially leading to more significant gains for the farmers by focusing on the proximity of their connections.

With the introduction of signal selection based on geographic proximity, the average distance for received signals dramatically decreases by over 90%. Specifically, at the 95th quantile, the average distance for a signal in the expanded network, which stood at 93.21 miles without signal selection, decreases to 6.69 miles when implementing signal selection (as Panel C, Column 2 shows). This significant reduction in distance leads to a 29% increase in the precision of the

---

17 We further investigated the distribution’s tail by examining statistics for the 90th percentile within each quantile of the distribution. Table 2 includes these extreme statistics for farm characteristics. Farms at the far right tail of the distribution are, on average, 14.79 miles away from their peers, have experienced 2,460 cumulative GDDs, and have received network signals that are over three times more precise than those received by farmers at the lower quantiles.

18 Figure 5 in Appendix D shows the distribution of gains for the expanded network.
network signal.

The impact of signal selection is particularly large at the lower quantiles. For example, at the $5^{\text{th}}$ quantile, signal precision increases from 0.26 without signal selection to 0.96 with signal selection, marking close to a threefold improvement. This suggests that the lower quantiles benefit the most from this signal selection methodology. This approach, which prioritizes proximity over other farm characteristics, enhances the relevance of the information exchanged within the network.

The introduction of signal selection significantly boosts the benefits farmers derive from network participation. Specifically, at the lowest quantile (the $5^{\text{th}}$), gains escalate from $93$ per acre to $148$ per acre, a 59% increase. For the highest quantile, gains increase from $539$ per acre to $688$ per acre, a 28% improvement. A comparison of the gains under the original SIRAC network against those achieved with the expanded network incorporating signal selection reveals even more striking enhancements—a 34% increase at the highest quantile and a 74% at the lowest quantile.

These findings highlight the critical importance of signal selection in network design, demonstrating that even a basic criterion for signal selection can lead to substantial economic benefits. Furthermore, we can refine the method for selecting signals, such as by incorporating additional farm characteristics, including the accuracy of peer farmers’ scouting technology.

### 5.3 Extreme Heat Simulation: The Network Adaptation Value

In this section, we explore the farmer’s network’s potential to mitigate yield losses from accelerated pest infestations caused by climate change. We define the adaptation value of the network as the additional economic gain from network participants in a scenario where the number of GDDs increases due to climate change. This adaptation value stems from two key mechanisms.

First, the network functions as an early-warning system for pest infestations triggered by a warmer climate. Second, the uncertainty regarding the optimal timing of pesticide application tends to rise with higher degree days, owing to the spatial variability in climate change. Even within a state, certain areas may be affected differently during warmer seasons. As the challenge of managing pests becomes more complex for farmers, the ability to learn from peers becomes increasingly valuable.

Climate change can accelerate the growth rates of pest populations in a given location and facilitate the emergence of pests that are more prevalent in warmer climates [Bale et al. (2002), Fand et al. (2012), and Skendžić et al. (2021)]. For instance, in the case of the ECB, an increase in GDDs can result in the early emergence of the first occurrence of the pest, a swifter growth in pest population, and an overall rise in the number of ECB generations on a farm [Kocmánková et al. (2010), Gagnon et al. (2019), Gagnon et al. (2019), Skendžić et al. (2021), and Schneider et al. (2022)].

Researchers from Iowa State Extension have shown that there can be up to four generations of ECB during a single season in warmer southern states. In the corn belt, however, there are typically two or three generations of ECB in a season. Failure to manage the first generation of ECB in a timely manner not only increases the damage caused by the initial generation but also raises the risks of further losses from subsequent ECB generations. Managing the ECB pest
promptly becomes even more important in warmer climates.\textsuperscript{19}

We assess how participation in agricultural networks can serve as an adaptation strategy to climate change by examining three distinct scenarios that project increases in GDD by 10\%, 20\%, and 30\%. These scenarios draw upon historical data observed by the Environmental Protection Agency (EPA) in the United States, which documents a significant rise in GDD nationwide from 1984 to 2020.\textsuperscript{20} The EPA’s findings reveal an average increase of 9\% in GDD over this 36-year timeframe, with certain regions experiencing jumps of over 20\%. This analysis aims to understand the adaptive benefits that network participation might offer in response to varying degrees of climate-induced changes in agricultural conditions.

Our simulation specifically targets the extreme value of GDDs under each climate change scenario to evaluate the maximum potential of the network for adapting to and mitigating severe pest infestations. We characterize extreme GDDs as values exceeding two standard deviations from the mean. Given the nonlinear increase of pest population growth rates with GDDs, we predict only moderate adaptation benefits from within-network learning at median GDDs values. We verify this prediction in simulations reflecting an average increase in the median number of GDDs.\textsuperscript{21} Furthermore, it is important to note that pest carrying capacity, which is the maximum pest population that can survive given the environmental and ecological constraints, naturally limits the impact of GDDs on pest populations. Therefore, we anticipate that the adaptive benefits provided by the network participation will likely diminish at higher GDD values. Our simulations aim to explore these boundaries, identifying the point at which the network’s adaptive benefits start to decrease as GDD increase.

In our climate change simulation, we adopt a distinct approach for measuring the adaptation value of the network, diverging from the methods used in our initial simulations. To quantify the network adaptation value, we employ a differences-in-differences (DiD) strategy. This process involves two primary steps:

1. First Difference: We start by computing the difference in gains from scouting activities, with and without the impact of climate change, across 10,000 simulations. This represents the initial variation in outcomes attributable to climate change alone.

2. Second Difference: Next, we calculate the gains from combining scouting and networking activities, both with and without the influence of climate change. This step assesses the combined effect of networking and scouting in the context of climate change.

We then determine the adaptation value of the network by the difference between these two measures: the gain from combining scouting and networking versus the gain from scouting alone. Essentially, our outcome variable in the climate change simulations reflects the expected gain from participation in networks, contrasting conditions with and without climate change, specifically focusing on the upper tail of the GDDs distribution.

Figure 4 shows the results of climate change simulations for the expanded network, focusing

\textsuperscript{19} Ecology and management of ECB in Iowa field corn, Iowa State Extension, 2017: https://store.extension.iastate.edu/product/15141


\textsuperscript{21} Simulation results spanning the entire distribution of GDDs under the three climate change scenarios are available upon request from the authors.
on a scenario that predicts a 10% increase in GDDs. In this figure, the blue histograms illustrate the distribution of differences in farmers’ expected gains from scouting activities alone. This comparison is made between the scenario with a 10% increase in GDDs and the baseline scenario, which assumes no change in climate. Conversely, the orange histograms depict the distribution of differences in farmers’ expected gains when integrating scouting and network signals, with the same comparison between the post-10% GDDs increase scenario and the climate unchanged baseline.

Figure 4 shows the climate change simulation results for the expanded network for the climate change scenario with an 10% increase in GDDs. The blue histograms represent the distribution of differences in farmers’ expected gains from scouting alone, comparing the scenario after a 10% increase in GDDs to the baseline scenario without climate change. Meanwhile, the orange histograms show the distribution of differences in farmers’ expected gains from combining scouting and network signals, again comparing the post-10% GDDs increase scenario to the no climate change baseline. The dashed vertical lines in each graph mark the median value of the distributions.

Graph A of Figure 4 shows the adaptation value of the expanded network under conditions of extreme GDDs, specifically when both scouting technology and network signal precision are

22 Appendix D presents the simulation results for the original SIRAC network.
low. The key metric for assessing adaptation value is the difference between the mean values of the orange and blue distributions, denoted by dashed vertical lines. In this scenario, the expected adaptation value of the network is approximately $40 per acre, or around 40% of the expected network gain under normal climatic conditions. This result shows that, even with low precision in learning mechanisms, the network still offers significant value in scenarios characterized by extreme GDDs and a heightened risk of severe pest infestations.

Graph B of Figure 4 illustrates a scenario in which the precision of the network signals has been enhanced, leading to an increase in the adaptation value of the expanded network to $60 per acre. This increase in adaptation value highlights the importance of the network for farmers facing potentially severe pest infestations, especially when other reliable sources of pest management information are lacking. By comparing the outcomes presented in Graphs A and B, we can quantify the benefits of enhancing network signal precision across all farms. The difference, representing an expected gain of approximately $20 per acre, represents the value derived from investing in the improvement of network signal precision.

Graphs C and D from Figure 4 present the outcomes of simulations where scouting technology precision is uniformly high across all farms within the network. Although the real-world likelihood of every farm having access to such high-precision scouting is small, analyzing this scenario is informative about the lower bound for the network’s adaptation value.

In scenarios where farms have advanced internal capabilities for monitoring pest populations, the incremental benefit of external information received from network peers naturally diminishes. The simulation results presented in Graph C, where the expected adaptation value of the expanded network—given high precision in scouting technology but low precision in network signals—is relatively modest, at about $25 per acre, reflects this phenomenon. When we enhance the precision of the network signal, the expected adaptation value of the network sees only a slight increase to approximately $40 per acre, as shown in Graph D. These findings highlight that even under a more conservative scenario where all farms have high scouting technology, there remains a discernible but marginal adaptation value in learning from network peers.

The Distribution of Network Adaptation Values

Table 3 details the adaptation values associated with network participation across five quantiles, considering three climate change scenarios (GDD + 10%, GDD + 20%, and GDD + 30%) and three different networks (SIRAC, expanded network, and expanded network with signal selection). The simulation focuses on extreme GDD within each climate change scenario. Table t:climatechangesim includes the corresponding GDD for each quantile of the adaptation value distribution.

A significant finding from this analysis is the substantial variation in adaptation values across the distribution for each network simulation and climate change scenario. At the lower end of the spectrum, adaptation values are relatively modest, ranging from $10 to $42 per acre across the various climate change scenarios for the SIRAC network, as noted in Panel A of Table t:climatechangesim. In stark contrast, at the highest quantiles, the adaptation value for the scenario with a 10% increase in GDDs climbs to $588 per acre. This value further escalates to $828 per acre under the more severe climate change scenario.

We can primarily attribute the variation in adaptation values across quantiles to two factors: the initial pest population levels and the magnitude of extreme GDD. Other simulation parame-
ters, such as corn prices and yields, remain consistent across quantiles. These results highlight the role of farmer networks in providing adaptive benefits under scenarios of heightened climate stress, particularly when the risk of severe pest infestations is elevated.

The simulation results for the expanded SIRAC network show only marginal increases in adaptation values compared to the original SIRAC network, aligning with our observations under normal climatic conditions. This outcome, which Panel B of Table 3:climatechangesim details, suggests that merely expanding the number of farms within a network—without addressing the variability in the precision of information (signals) shared among network members—yields only modest enhancements in the network’s adaptation value. This finding underscores the limited effectiveness of network expansion as a standalone strategy for improving adaptation to climate change.

Table 3: Network Adaptation Value for Extreme Heat Scenarios

<table>
<thead>
<tr>
<th></th>
<th>GDD + 10%</th>
<th></th>
<th>GDD + 20%</th>
<th></th>
<th>GDD + 30%</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adaptation Value</td>
<td>Extreme GDD ($ per acre)</td>
<td>Adaptation Value</td>
<td>Extreme GDD ($ per acre)</td>
<td>Adaptation Value</td>
<td>Extreme GDD ($ per acre)</td>
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<td></td>
</tr>
<tr>
<td>A. SIRAC Network</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q5</td>
<td>9 (5)</td>
<td>2,775</td>
<td>20 (9)</td>
<td>2,880</td>
<td>24 (13)</td>
<td>3,043</td>
</tr>
<tr>
<td>Q25</td>
<td>74 (4)</td>
<td>2,767</td>
<td>124 (6)</td>
<td>2,925</td>
<td>158 (6)</td>
<td>3,067</td>
</tr>
<tr>
<td>Q50</td>
<td>154 (7)</td>
<td>2,818</td>
<td>221 (5)</td>
<td>2,944</td>
<td>272 (6)</td>
<td>3,099</td>
</tr>
<tr>
<td>Q75</td>
<td>270 (8)</td>
<td>2,914</td>
<td>331 (7)</td>
<td>3,055</td>
<td>378 (8)</td>
<td>3,155</td>
</tr>
<tr>
<td>Q95</td>
<td>413 (17)</td>
<td>3,062</td>
<td>451 (8)</td>
<td>3,110</td>
<td>466 (7)</td>
<td>3,197</td>
</tr>
<tr>
<td>B. Expanded Network</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q5</td>
<td>9 (4)</td>
<td>2,744</td>
<td>28 (6)</td>
<td>2,878</td>
<td>46 (5)</td>
<td>3,010</td>
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<tr>
<td>Q25</td>
<td>79 (3)</td>
<td>2,784</td>
<td>127 (5)</td>
<td>2,937</td>
<td>173 (8)</td>
<td>3,077</td>
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<tr>
<td>Q50</td>
<td>111 (7)</td>
<td>2,815</td>
<td>210 (9)</td>
<td>2,956</td>
<td>312 (14)</td>
<td>3,094</td>
</tr>
<tr>
<td>Q75</td>
<td>264 (13)</td>
<td>2,900</td>
<td>421 (14)</td>
<td>3,052</td>
<td>574 (21)</td>
<td>3,199</td>
</tr>
<tr>
<td>Q95</td>
<td>561 (39)</td>
<td>3,087</td>
<td>816 (61)</td>
<td>3,183</td>
<td>873 (33)</td>
<td>3,311</td>
</tr>
<tr>
<td>C. Expanded Network with Signal Selection</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q5</td>
<td>10 (1)</td>
<td>2,738</td>
<td>25 (4)</td>
<td>2,875</td>
<td>61 (8)</td>
<td>3,016</td>
</tr>
<tr>
<td>Q25</td>
<td>81 (0)</td>
<td>2,781</td>
<td>158 (7)</td>
<td>2,918</td>
<td>249 (11)</td>
<td>3,050</td>
</tr>
<tr>
<td>Q50</td>
<td>166 (6)</td>
<td>2,812</td>
<td>298 (10)</td>
<td>2,981</td>
<td>439 (10)</td>
<td>3,108</td>
</tr>
<tr>
<td>Q75</td>
<td>325 (10)</td>
<td>2,876</td>
<td>486 (13)</td>
<td>3,012</td>
<td>678 (22)</td>
<td>3,171</td>
</tr>
<tr>
<td>Q95</td>
<td>680 (9)</td>
<td>3,104</td>
<td>916 (9)</td>
<td>3,215</td>
<td>1128 (69)</td>
<td>3,448</td>
</tr>
</tbody>
</table>

Note: Table 3 presents the simulation results for the adaptation value of network participation by quantiles for three climate change scenarios. The adaptation value is the additional expected gain of network participation under a climate change scenario. All simulation results are for the extreme GDD within each climate change scenario. Extreme GDD is defined as GDD two standard deviations above the mean of the distribution.

However, the introduction of a signal selection mechanism, which prioritizes signals based on geographical proximity, marks a noticeable improvement in the network’s adaptation capabilities. With this mechanism in place, the adaptation value of the network, especially at the higher quantiles of the distribution, sees a considerable increase. Notably, under a climate change scenario that projects a 20% increase in GDDs, the adaptation value for the network employing signal selection jumps to $911 per acre (Panel C of Table 3:climatechangesim). This improvement is par-
ticularly pronounced in the top quantiles, highlighting the benefits of targeted signal selection in enhancing the network’s adaptation value in the face of more severe climate-induced challenges.

The simulation outcomes for scenarios of extreme heat reveal the ecological constraints that naturally limit the impact of climate change on pest infestations. These constraints are primarily dictated by the pest carrying capacity, which serves as an upper threshold for pest population growth. Beyond this ecological limit, further increases in temperature do not significantly exacerbate potential losses from pest infestations, nor do they substantially enhance the adaptation benefits of network participation.

This dynamic is evident in the progression of adaptation values across varying degrees of climate change severity. The adaptation value sees more significant increases as scenarios shift from moderate (GDD + 10%) to severe (GDD + 20%). However, the transition from a severe to an extreme climate change scenario (GDD + 30%) does not yield a proportional increase in adaptation value. This pattern suggests that there is a diminishing return on the adaptation value of network participation as climate change intensifies beyond certain ecological thresholds for pest growth.

6 Conclusions

We assess the economic value of farmer networks in enhancing pest management by adapting an economic model of learning to pest management and simulating this adapted model across variations of the SIRAC network. Our findings reveal considerable variability in the network’s value, both under typical climate conditions and during extreme heat events caused by climate change. Networks prove especially beneficial for farmers most at risk of pest infestations, with their value in mitigating the impacts of extreme heat on pest infestations exceeding $900 per acre.

This analysis provides insights for policymakers and businesses aiming to foster the development and expansion of such networks. We identify three primary observations from our simulations that could guide the design of future networks and suggest directions for additional research:

Variable Network Gains: The gain from network participation varies widely among farmers, indicating the potential for differentiated pricing strategies. Some farmers might pay more for network access, while others may require subsidies. Simulations could help determine optimal pricing strategies.

Strategic Network Expansion and Signal Selection: Expansion benefits are limited without signal selection. Our findings suggest that enhancing the network with a thoughtful signal selection mechanism, potentially based on geographical proximity and other farm characteristics (e.g., crop rotation, climate, soil attributes), could maximize the network’s value. Future simulations could explore which farms would benefit most from joining the network based on these refined criteria.

Complementary Role with Insurance: The network’s role as an early warning system for pest infestations could synergize with agricultural insurance policies, especially as climate change leads to warmer growing seasons. By mitigating extreme outcomes, the network could reduce potential losses and, consequently, insurance premiums. Extending the model to include multiple pests and their distinct life cycles could reveal even greater economic benefits of network participation.
Acknowledgments: The authors would like to thank the researchers who contributed to the SIRAC project at the annual meetings. Their comments and suggestions greatly improved this paper. Special thanks go to Asheesh Singh for his ongoing support and helpful contributions. Additionally, the authors are grateful for the assistance provided by supporters from the Iowa Soybean Association (ISA), including Peter Kyveryga, Matthew Carroll, and Aaron Prestholt, who provided significant support for this research. The authors also acknowledge the financial support received from the U.S. National Science Foundation (NSF) and Hatch funding from the Center for Agricultural and Rural Development (CARD) at Iowa State University which helped make this research possible.


Rosenzweig, C., Iglesius, A., Yang, X.-B., Epstein, P. R., and Chivian, E. (2001). Climate change and extreme weather events-implications for food production, plant diseases, and pests.


Appendix A: Learning Model Derivations

Our learning model is constructed based on the target input model, which is a widely used framework in the economics of learning through networks. The model’s core idea is farmers’ opportunities to learn from their peers about the optimal timing for pesticide application. The optimal timing for pesticide application is a crucial aspect that farmers seek to learn about, as it directly impacts their ability to mitigate pest infestations. Our model assumes that this optimal timing comprises two components.

The first component, denoted as $\mu_i$, represents random noise that is unpredictable by farmers. In our model, we assume this noise term follows an independent and identically distributed (i.i.d.) normal distribution $N(0, \vartheta^2)$. The optimal timing, denoted as $\tau$, represents the most profitable choice for farmers. However, since this is initially unknown, farmers strive to learn and subsequently select the optimal timing, denoted as $\tau^*$, to minimize losses caused by agricultural pests.

The second component, $\tau^*$, represents the universal optimal timing across farms. Given their individual knowledge and experience levels and prior information, farmers decide the timing of pesticide application, denoted as $\tau_{it}$, and the new information update from learning channels reduces the noise around optimal timing.

$$\tilde{\tau}_i = \tau^* + \mu_{it} \quad (1)$$

Farmers update their prior beliefs about the target $\tau^*$ based on their observations of pest populations. This process involves using their own observations and information from their peers to refine their understanding of the optimal timing for pesticide application.

Where $\mu_{i,t} \sim N(0, \vartheta^2)$. The farmer’s production increases as they learn and choose a treatment time closer to the optimal time $\tau^*$.

Let’s denote the population of the pest at the very first season as $P_0 \sim N(\mu_{P_0}, \vartheta_{P_0}^2)$ which is normally distributed. We also define the pest population function as:

$$P_t = e^{r \Delta GDD_{t,t-1}}P_{t-1} = e^{r GDD}P_0 \quad (2)$$

Therefore, $P_t$ is normally distributed with mean of $\mu e^{r GDD}$ and variance of $\vartheta_{P_0}^2 e^{2r GDD}$. The variable $r$ in the production function indicates the pest’s intrinsic growth rate, which is defined as the difference between pest growth $g$ and the pest death rate $\delta$. In a given week the farmers scout and revise their information on the pest population to determine the treatment timing. For the observational data we have $P_t \sim N(\mu_{P_t}, \vartheta_{P_t}^2)$ and for the prior we have $P_t \sim N(\mu_{P_{t-1}}, \vartheta_{P_{t-1}}^2)$.

We define the farmer’s production function is defined as follows:

$$q_i(\tau) = \bar{q}_i - \alpha g(GDD)(\tilde{\tau}_i - \tau)^2 \quad (3)$$

This production function measures the deviations from the maximum potential yield stemming from the gap between the optimal time of pesticide application and the farmer’s actual choice. The second term in the equation can be interpreted as a loss function, which is proportional to the pest growth, and the pest growth is a function of the accumulated growing degree days. The term $\alpha g(GDD)$ is a loss multiplier proportional to the pest growth rate. The pest growth rate $g(GDD)$ is a solution for the pest population function defined as differential equation $\frac{dP}{dt} = rP(1 - \frac{P}{\kappa})$. In the pest population function, $\kappa$ indicates the pest’s carrying capacity.

To derive the optimal timing of the pesticide application, we take the expectation of equations 1 and 3:

$$\tau_{i,w} = E(\tilde{\tau}_{i|P_{i,w}}) = \tau^*$$

and,

$$E(q_i(\tau)) = \bar{q}_i - \alpha g(GDD)(\vartheta_{\tilde{\tau}_i}^2 + \vartheta_{\mu_{it}}^2) \quad (4)$$
The equation (4) shows the farmer's expected gain in production as a function of two variances. The first one is the variance of the latest time for pesticide application \( \rho_i \), which farmers can change by learning and maximizing their profit through learning from their own experience and also receiving signals from the information neighbors. The second is the noise variance, which can be higher for the farmers with more experience and knowledge. Therefore, the farmers need to learn about the most profitable time.

\[
\vartheta_i^2 = \frac{1}{\sigma_i^2} + \frac{1}{\sigma_{i|\rho_i}^2 + \sigma_{i|\rho_i}^2 \rho_{r,p}^2}
\]

Using Bayes rule for the variances, we derive the posterior variance:

\[
\vartheta_{i|\rho_i}^2 = \frac{\vartheta_i^2 \vartheta_{i|\rho_i}^2}{\vartheta_i^2 + \vartheta_{i|\rho_i}^2} = \frac{\vartheta_i^2 \vartheta_{i|\rho_i}^2}{\vartheta_i^2 + \vartheta_{i|\rho_i}^2 \rho_{r,p}^2} + 1 \vartheta_{i|\rho_i}^2
\]  

Therefore, the equation (10) shows the farmer's expected gain in production as a function of two variances. The first channel is \( \rho_i \), the precision of the farmer's initial estimate of the pesticide application time, which can be higher for the farmers with more experience and knowledge. Therefore, the farmers need to learn and maximize their profit through learning from their own experience and also receiving signals from the information neighbors. The second channel is a channel of learning. Farmers with higher experience and knowledge can have a better initial estimate of the most profitable time, which can be higher for the farmers with more experience and knowledge. Therefore, the farmers need to learn and control it. Using Bayes rule and the farmer's prior about the latest time of pesticide application, we derive the equation for the variance.

\[
\vartheta_i^2 = \frac{1}{\sigma_i^2} + \frac{1}{\sigma_{i|\rho_i}^2 + \sigma_{i|\rho_i}^2 \rho_{r,p}^2}
\]

The variance of observational information is \( \vartheta_i^2 = \frac{1}{\sigma_i^2} + \frac{1}{\sigma_{i|\rho_i}^2 + \sigma_{i|\rho_i}^2 \rho_{r,p}^2} \), and the variance of the prior can be written as \( \vartheta_i^2 = \frac{1}{\sigma_i^2} + \frac{1}{\sigma_{i|\rho_i}^2 + \sigma_{i|\rho_i}^2 \rho_{r,p}^2} \), where \( \rho_{r,p} \) is the correlation coefficient between optimal timing \( \tau \) and the pest population \( P_i \).

We use the Bayes rule for the variances the derive the posterior variance:

\[
\vartheta_{i|\rho_i}^2 = \frac{\vartheta_i^2 \vartheta_{i|\rho_i}^2}{\vartheta_i^2 + \vartheta_{i|\rho_i}^2} = \frac{\vartheta_i^2 \vartheta_{i|\rho_i}^2}{\vartheta_i^2 + \vartheta_{i|\rho_i}^2 \rho_{r,p}^2} + 1 \vartheta_{i|\rho_i}^2
\]

Therefore, the conditional variance of \( \tau_i \) can be calculated as

\[
\vartheta_{i|\rho_i}^2 = \frac{1}{\sigma_i^2} + \frac{1}{\sigma_{i|\rho_i}^2 + \sigma_{i|\rho_i}^2 \rho_{r,p}^2} \vartheta_{i|\rho_i}^2
\]

Using Bayes rule for the variances, we derive the posterior variance \( \vartheta_{i|\rho_i}^2 \) as follows:

\[
\vartheta_{i|\rho_i}^2 = \frac{\vartheta_i^2 \vartheta_{i|\rho_i}^2}{\vartheta_i^2 + \vartheta_{i|\rho_i}^2} = \frac{1}{\sigma_i^2 + \sigma_{i|\rho_i}^2 + \sigma_{i|\rho_i}^2 \rho_{r,p}^2}
\]

If we have \( N_p \) prior observations on pest population from scouting we can rewrite the equation as follows:

\[
\vartheta_{i|\rho_i}^2 = \frac{1}{\sigma_i^2 + \sigma_{i|\rho_i}^2 + \sigma_{i|\rho_i}^2 \rho_{r,p}^2} \vartheta_{i|\rho_i}^2
\]

Define the precision as: \( \rho_0 = \frac{1}{\sigma_i^2 \vartheta_{i|\rho_i}^2} \) and \( \rho_S = \frac{1}{\sigma_{i|\rho_i}^2} \) we have:

\[
\vartheta_{i|\rho_i}^2 = \frac{1}{\rho_0} + \gamma \times \rho_S
\]

Where \( \gamma = \frac{N_p}{1 - \frac{\rho_{r,p}^2}{\sigma_i^2 + \sigma_{i|\rho_i}^2}} \).

Equation (10) shows that the farmers have two main channels to reduce the variance. The first channel is \( \rho_0 \), the precision of the farmer’s initial estimate of the pesticide application time, which can be higher for the farmers with more experience and knowledge. Therefore, the farmers with higher experience and knowledge can have a better initial estimate of the most profitable time of pesticide application, which can translate to higher profit.

The second channel is a channel of learning. \( \rho_S \) is the precision of the farmer’s technology to learn about the most profitable time.

Therefore the farmers’ expected gain in production can be written as follows:

\[
E(q_i|\tau_i) = q_i - \alpha g(GDD)(\frac{1}{\rho_0} + \gamma \times \rho_S + \vartheta_{i|\rho_i}^2)
\]

**Learning through network:**

In this section, We derive the farmers’ expected gain from learning through three channels. We assume that the farmers are connected to a network and have an additional medium to gain information about the most profitable time for pesticide application. Farmer \( i \) receives multiple
signals from several information neighbors. For simplicity, we assume all signals are similar in terms of precision level. In the application section, we relax this assumption and assume that the signals are heterogeneous. We also assume that the received signals are not correlated, meaning that $\text{cov}(\mu_i, \mu_j) = 0, \forall i, j$, and $\text{cov}(\mu_j, \mu_{-i}) = 0$ and farmers make inference about the treatment time of the pesticide application by updating the priors about the most profitable application time. Following similar steps in the previous section, we can derive the variance of the application time as follows:

$$\vartheta_i^2 = \frac{1}{\rho_0 + \gamma \times \rho_S + N \times \rho_N}$$ (12)

Where $N$ in the equation [12] indicates the number of signals each farmer receives and, $\rho_N$ shows the precision of the signals and thus, $N \times \rho_N$, in the denominator reflects captures the learning from network channel.

Therefore, the value of learning can be measured using the equation [13]:

$$\Delta = E(\pi^*_i|\text{with social learning}) - E(\pi^*_i|\text{without social learning})$$

$$= \alpha g(GDD) \left[ \frac{1}{\rho_0 + \gamma \times \rho_S + N \times \rho_N} - \frac{1}{\rho_0 + \gamma \times \rho_S} \right]$$ (13)

**Farmer’s expected gain under climate change:**

In the simulations for the climate change scenarios, we create a DiD variable, as explained in section 5.3. Our DiD outcome variable is defined by simulating equation [13] for the extreme heat values with and without climate change:

$$\Delta_{\text{DiD}} = \Delta_{\text{CC}} - \Delta$$ (14)

Where $\Delta_{\text{CC}}$ captures the simulated value of the learning from the network for extreme heat values and $\Delta$ is the simulated value of the learning from the network without climate change.
Appendix B - Corn Pests

Corn Rootworm

The western and northern corn rootworms pose significant challenges to maize production in the Midwest, causing estimated annual losses exceeding $1 billion in yield and management costs in the United States. Recent assessments suggest that current losses may be even higher. Corn rootworm larvae, hatching from late May through early June and feeding until late July, primarily damage maize by feeding on roots, leading to yield reductions of approximately 15-17% per node of root damage. This larval feeding can result in severe lodging, further decreasing grain yield by 11-34%. Research indicates a broad range of yield losses, from 6% to 30%, for one to two nodes of root injury, with a notable study finding a 17.9% yield loss per node of roots injured. Under moderate infestation levels, a 15% yield loss could mean a reduction of 30 bushels per acre, assuming a potential yield of 200 bushels per acre. Management practices, such as selecting resistant seed varieties, are crucial in controlling corn rootworm populations.

Corn Earworm

The corn earworm, a migratory pest from the southern and southeastern U.S., poses a threat to Iowa’s corn, especially the second flight arriving in late July. This pest can infest over 50% of plants in late-planted fields, leading to significant yield losses. Despite severe injuries reported in fields planted with pyramided Bt hybrids, resistance in the Midwest is not yet confirmed. Insecticide applications, guided by pheromone trap catches, are recommended for sweet corn or late-maturing fields to mitigate losses. The corn earworm’s life cycle is about 30 days, with the number of generations varying by latitude, indicating a need for vigilant monitoring and timely interventions.

Western Bean Cutworm

The western bean cutworm, traditionally considered a secondary pest, can cause considerable economic damage in favorable conditions, with yield losses estimated between 4 and 15 bushels per acre per larva. Infestations can reduce grain yield by 30 to 40 percent in cases of several larvae per ear. Scouting for eggs and larvae is critical as bio-tech traits offer limited control, and the timing of insecticide applications is crucial to prevent larvae from entering the ear and causing damage. Pheromone trapping is a valuable tool for monitoring adult flights and determining the optimal timing for insecticide application. Additionally, this pest increases the risk of ear rot and reduced grain quality, highlighting the importance of monitoring and treating infestations to maintain grain quality and mitigate economic losses.

European Corn Borer

The European corn Borer (ECB), Ostrinia nubilalis, is an insect primarily found in western Asia and Europe. The ECB caterpillars feed on the corn plant causing severe yield losses. In the early 1900s, U.S. farmers in Massachusetts first encountered infestations of ECB, which quickly spread to the Midwest and western states. Iowa farmers first observed ECB infestations in 1942, leading to substantial yield losses in the state. Before the introduction of transgenic corn hybrids in the mid-1990s, ECB infestations resulted in yield losses and pest control costs amounting to one billion dollars annually for U.S. farmers [Hodgson and Rice (2017)]. The widespread adoption of Bt-corn, a transgenic corn hybrid, led to a drastic decline in ECB populations throughout the United States. However, U.S. farmers have been gradually increasing planting of non-Bt corn varieties to approximately 17% of total U.S. corn production. Furthermore, ECB has become increasingly more resistant to Bt toxins in corn and to insecticides, particularly in the Midwest where Bt Corn was widely adopted by farmers (reference). As a result, some areas in the Midwest have witnessed a resurgence in the ECB population (reference).
ECB Population Dynamics and Yield Losses

The lifecycle of ECB consists of four distinct stages: egg, larva (borer or caterpillar), pupa, and adult (moth). The completion of these stages represents one generation. The larvae of ECB go through five molts, or instars, during their development. With each molt, the larvae shed their skin and increase in size. In the United States, the European corn Borer (ECB) exhibits varying numbers of generations per season depending on the region and climate. While the ECB can have up to six generations per season in some areas, the number of generations is typically lower in the United States, with up to four generations observed. In Iowa, where the climate is influenced by summer temperatures, there are typically two generations of ECB each season. However, in years with longer and warmer summers, there is a possibility of a partial third generation occurring.

The ECB development and the resulting population growth depends significantly on the climate, more specifically on the accumulation of degree-days above the ECB development temperature of 50°F. The eggs of ECB are typically laid in irregular clusters containing around 15 to 20 eggs. The developmental threshold for egg hatching is approximately 15°C, and eggs usually hatch within four to nine days. During the winter, ECB larvae enter a diapause state and survive by remaining in cornstalks, corn cobs, corn residue, or weed stems. Development resumes when temperatures rise above 50°F. Farmers can predict the development of ECB through its four life stages by tracking the cumulative number of degree days starting from the capture of adults in the spring using traps. For example, the first generation of ECB larvae start corn stalk boring approximately 435 accumulated degree-days after the detection of the first spring ECB adult (Hodgson and Rice, 2017). The first instar of the second generation ECB larva occurs with about 1,404 accumulated degree-days.

The ECB larval feeding injuries the corn plant reducing grain production. Table 4 shows the potential corn yield loss from ECB infestation at different stages of corn development. Yield losses are expressed in terms of percentage reduction in bushels per acreage. The magnitude of the yield loss is depends on the developmental stage of the corn plant and the average larval density during an ECB infestation. For example, at the early whorl state, the potential yield loss from an ECB infestation ranges from 5.5 to 10% as the density of ECB larva increases from one to three larva per plant (reference here). ECB infestations can potentially reduce corn yields by 12%.

Table 4: Corn Yield Loss from ECB Infestation by Corn Growth Stage

<table>
<thead>
<tr>
<th>Corn growth stage</th>
<th>One larva/plant</th>
<th>Two larva/plant</th>
<th>Three larva/plant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early whorl</td>
<td>5.5%</td>
<td>8.2%</td>
<td>10.0%</td>
</tr>
<tr>
<td>Late whorl</td>
<td>4.4%</td>
<td>6.6%</td>
<td>8.1%</td>
</tr>
<tr>
<td>Pre-tassel</td>
<td>6.6%</td>
<td>9.9%</td>
<td>12.1%</td>
</tr>
<tr>
<td>Pollen Shedding</td>
<td>4.4%</td>
<td>6.6%</td>
<td>8.1%</td>
</tr>
<tr>
<td>Blister</td>
<td>3.0%</td>
<td>4.5%</td>
<td>5.5%</td>
</tr>
<tr>
<td>Dough</td>
<td>2.0%</td>
<td>3.0%</td>
<td>3.7%</td>
</tr>
</tbody>
</table>

Note: Table 4 shows potential corn yield loss computed by Christian H. Krupke, 2017, accounting for physiological stresses but excluding factors such as stalk or ear breakage. Yield losses are expressed as a percentage of corn yield.
**ECB Pest Management**

**Monitoring and Scouting.** Farmers can use monitoring methods to predict the ECB population in their fields. ECB moths can be monitored using black light and pheromone traps, with both methods providing correlated catches. Pheromone traps specifically attract male moths, while black light traps capture both male and female moths. Although black light traps are generally more reliable, they can also capture a large number of other insects, requiring extensive sorting efforts. Among the monitoring techniques, pheromone-baited water pan traps have been found to be the most efficient in capturing adult moths (reference?). In addition to adult capture methods, there are alternative techniques to estimate borer phenology. For example, plant phenology, which refers to the timing of specific developmental stages in plants, can be utilized to predict corn borer development. Thermal summations, which involve calculating accumulated heat units, have also proven to be highly predictive.

Scouting complements monitoring in helping farmers determine the need for and the timing of pesticide applications. Trap catches serve as an indicator to initiate thorough scouting in the field for the presence of egg masses, as there is only a weak correlation between moth catches and population density. Hodgson and Rice (2017) highlights the value of scouting for ECP management: "Attempting to manage European corn borer without scouting is often economically ineffective and may result in wasted application costs." However, scouting can also be costly. For first generation ECB, farmers must scout for larvae. The Iowa Station Extension recommends "sampling from five representative sets of 20 consecutive plants every 40 to 50 acres". For second generation ECB, farmers scout for egg masses to assess the density of the egg population. Farmers must sample several locations within their fields to estimate the density of eggs and calculate the cost and benefits of pesticides application.

**Insecticides.** Liquid formulations of insecticides are commonly utilized to protect corn crops from damage, particularly during the period from early tassel formation until the corn silks have dried. The recommended application strategies for liquid insecticides can vary, ranging from a single application prior to silking to weekly applications. Granular formulations have gained popularity as an alternative to liquid insecticides. These granules can be placed directly into the whorl, leading to effective control of first-generation larvae, as they tend to congregate in this area. Moreover, insecticide applied in a granular formulation tends to have greater persistence (reference).

The timing of insecticide application is critical for ECB control. The timing of liquid applications is typically aligned with egg hatch to prevent infestation. However, if corn borers are already present in a field, the critical treatment time shifts to just before tassels emerge or at the moment of tassel emergence from the whorl. This specific growth stage is crucial because the larvae are actively moving and are more likely to come into contact with the insecticide. For second generation ECB, the timing of application is also critical as insecticides must be applied before the larvae enter the corn stalk or ear (reference).

**Cultural practices.** The destruction of stalks, which serve as the overwintering site for corn borer larvae, has long been recognized as a critical component of corn borer management strategies (reference). Merely diskng the field is insufficient; plowing to a depth of 20 cm is necessary to effectively eliminate the larvae. Mowing the stalks close to the soil surface has proven highly effective, eliminating over 75% of the larvae. Combining mowing with plowing further enhances the efficacy of larval destruction. Tillage practices must also be considered in ECB management plans as leaving a significant amount of crop residue on the soil surface can actually promote borer survival.

**Host plant resistance.** Significant efforts have been devoted to breeding research aimed at developing resistance against corn borers, particularly in grain corn varieties that face ECB populations with a single annual generation. One of the key factors contributing to resistance in seedlings against young corn borer larvae is a chemical compound called DIMBOA. This compound acts as a repellent and deterrent to feeding by the larvae. However, incorporating the

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[23] Extension agencies such as the Iowa State University Extension department offer farmers templates and examples of cost-benefit analysis for pesticide applications. Such analysis depend not only on the egg density in the fields but also on an estimate for the expected ECB survivorship in the farm, the price of corn, and the cost of pesticide applications.
known resistance factors into sweet corn varieties has proven to be challenging. For example, in the case of sweet corn, it is difficult to maintain the desirable taste and texture while enhancing the plant resistance to ECB (reference).

**Bt-corn and resistance management.** Bt corn is a genetically modified corn plant engineered to contain genetic material from a toxin produced by the bacterium Bacillus thuringiensis var. kurstaki. This genetic modification leads to the expression of the toxin, making the plant toxic to ECB and closely related insects while posing no harm to other animals. The widespread cultivation of Bt corn has had a profound impact on the population dynamics of ECB (Burkness et al. (2001) and Hutchinson et al. (2010)). However, over time the ECB population within regions with widespread adoption of Bt-corn tend to develop resistance to the Bt toxins. In order to delay the development of Bt resistance, the industry requires Iowan farmers to create a refuge area withing their farm with non-Bt corn to induce mating between Bt-susceptible and Bt-resistant insects to delay the evolution process of Bt-resistant insects. Furthermore, farmers must account for multiple groups of Bt-corn components offering resistance to different insects and farmers when configuring their fields. The adoption of Bt-corn eliminates the need for insecticide applications reducing management costs but farmers must pay an additional technology fee for Bt-corn seeds.
Appendix C - Simulation

Simulations step-by-step

This document outlines the procedures for data preparation and simulation processes. Section C.1 provides detailed information on the data preparation. In Section C.2, the steps for simulating the value of learning within a small network comprising 121 farmers are explained. Section C.3 elaborates on the steps for the expansion of the network to 605 farmers and how simulations were conducted using the expanded network. Section C.4 provides details on the simulation of learning value derived from farmers’ expanded networks with signal selection criteria. Lastly, Section C.5 describes the simulation steps to simulate learning value within both small and large networks under various climate change scenarios.

C.1 Preparing the raw data sourced from Iowa Soybeans Association (ISA)

We obtained our raw data from ISA, which is formatted as .csv files. This data contains details about the number of traps installed on each farm linked to the SIRAC network, with a total of 121 farms interconnected within the network. In our simulations, we consider this network as the base network. Additionally, the dataset includes pairwise distances between farms, measured in meters. The pairwise distance in our small network varies from 0 to 274 miles with an average of approximately 114 miles and a standard deviation of 64 miles. We use these observations to create weights for the signal precision. In our simulations, we select 10 signal senders randomly without restricting the distance from the signal-receiving farmer. Later, for the signal selection models we will introduce specific criteria for the signal senders to provide insights on network design. For this section, the signal senders can be located anywhere within the network. We follow the following steps to prepare the data for our simulations:

C.1.1 Creating a unique identifier for each farm: This step is done in Excel. We assign unique identifiers ranging from 1001 to 1121. This is a required step before the simulations. We use unique identifiers to select the signal senders in each round of simulation. We use the _record_id in the raw data to assign the unique identifiers. The data also includes variable _record_id_2 for the paired farm. Each farm is paired with 120 farms and in total the raw data has 14,520 observations.

C.1.2 Simulating latitude and longitude: This step is necessary for creating maps to show the network. For this simulation, we consider the center of Iowa as a reference farm and simulate the location of other farms based on pairwise distance. To replicate the simulation, use our Python code to create latitude and longitude for each farm. This program simulates the latitude and longitude of 121 farms.

C.1.3 Calculate the precision of scouting for each farm: We use the number of traps installed in each farm to calculate this parameter. Number of traps ranges from 1 to 7. For each farm, we divide the number of traps by the maximum number of traps. (Example – If there are 4 traps installed in farm A then: Precision of scouting in Farm A = Number of traps in farm A/7).

C.1.4 Creating weights for signals: We use the pairwise distance for this purpose. First, we convert the distances from meters to miles. Then we assign a weight of 1 if the pairwise distance is less than or equal to 10 miles. If the pairwise distance is between 10 to 25 miles, we assign a weight of 0.75. If the pairwise distance is 25 to 50 miles, we assign a weight of 0.50, and finally, if the pairwise distance is more than 50 miles we assign a weight of 0.25.

C.1.5 Precision of signals: To calculate the precision of the signal we generate an interaction variable by multiplying the precision of scouting generated in C.1.3 and the weights generated in C.1.4 above. Later, in simulations we will use this variable to calculate the weighted average for the signals received by a farmer.

The output of this step is data with the following variables:
<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>id_sender</td>
<td>Unique identifier for signal-sending farms</td>
</tr>
<tr>
<td>id_receiver</td>
<td>Unique identifier for signal-receiving farms</td>
</tr>
<tr>
<td>traps_per_field_sender</td>
<td>Number of traps installed in the signal-sending farms</td>
</tr>
<tr>
<td>traps_per_field_receiver</td>
<td>Number of traps installed in the signal-receiving farms</td>
</tr>
<tr>
<td>precision_scout</td>
<td>Precision of scouting in signal-receiving farms</td>
</tr>
<tr>
<td>precision_signal</td>
<td>Precision of scouting in signal-sending farms</td>
</tr>
<tr>
<td>dist_miles</td>
<td>Distance from signal origins to destination farm (miles)</td>
</tr>
<tr>
<td>weight_signal</td>
<td>Signal weights</td>
</tr>
<tr>
<td>w_pr_sigl</td>
<td>Interaction variable (Signal × weights)</td>
</tr>
</tbody>
</table>

Simulated Geographic Coordinates

\[(Latitude_{sender}, Longitude_{sender})\] Simulated geographical location of signal senders

\[(Latitude_{receiver}, Longitude_{receiver})\] Simulated geographical location of signal receivers

Note: The output data should be saved as .csv. The simulations in Python code use the .csv as input data. To replicate, the Python code for importing the .csv file should be adjusted.
C.2 Simulating the value of learning within a small network

We use the data prepared in the previous step C.1, to simulate the value of learning within the small network. For our simulations, we have developed a Python program. Refer to our Python code to replicate the results:

C.2.1 Number of iteration: We set the number of simulations to 10001. Then, we create a loop to iterate through the following steps to simulate the value of the network.

C.2.1.1 Assigning values for the exogenous parameters: In this part of the simulation, we define our exogenous parameters. These parameters include the distribution of the pest’s initial population, distribution of pest carrying capacity, number of scouting, number of signals, distribution of corn price, distribution of corn yield, and distribution of growing degree days. We use the values outlined in Table 1 for this purpose. For parameters with distributions, we first generate a sample of 10,000 from the distribution, and then randomly select an observation from the sample.

C.2.1.2 Selecting Signal senders: In each simulation round, we randomly choose 10 farmers to act as signal senders, identified by their unique identifiers idsender. These selected signal senders are then excluded from the list of potential signal receivers, identified by their unique identifiers id.

C.2.1.3 High vs. Low Precision Signal: In each simulation, every farmer receives 10 signals, each weighted differently based on its distance from the signal origin. Table 1 provides details on the weights assigned to each signal. Using these weights, we compute the weighted average of these 10 signals for each of the 111 signal-receiving farmers.

High precision signal refers to the average of signals with precision greater than the median value for all of the 111 farmers. Conversely, low precision signal refers to the average of signals with precision less than the median value. Note: For the presentation of the results with graphs we used slightly different numbers of simulations for each sub-sample to keep the scales of the graph the same.

C.2.1.4 High vs. Low Precision Scouting: The sub-sample of signal-receiving farmers with low precision scouting is defined as the average scouting precision for the farms with the number of traps less than or equal to the median number of traps. On the other hand, our sub-sample for high-precision scouting is defined based on the values for scouting precision greater than the median number of pest traps.

C.2.1.5 High vs. Low Initial precision: For low initial precision, we assign a value of 0.14, while for high initial precision, we assign a value of 0.91. In the simulation of the theoretical model, we determined the 10th percentile and 90th percentile of the sample of 10,000 observations from a uniform distribution as the benchmarks for low and high initial precision, respectively. These values were utilized in the application part due to the absence of information regarding farmers’ initial knowledge and experience in our dataset.

C.2.1.6 Expected Gain From Network: In the final part of the simulation, based on the values of the parameters we simulate the equation 8 and calculate the farmer’s expected gain from learning through the network. The output of the simulation captures the difference between the farmer’s expected gain from three learning channels (i.e., initial knowledge and experience, scouting, and learning from their networks) and their expected gain as if they were not participating in the network.

C.2.2 Simulating Value of Learning for the Base Network under Climate Change Scenarios: For this part of the simulations, we repeat all the steps detailed in C.2.1 with two modifications.

First, we modify step C.1.1 and define three new distributions for the Growing Degree Days by shifting the mean of the distribution by 10%, 20%, and 30%. Then after creating a sample of 10,000 observations from each distribution, We focus only on the extreme values of the distributions. Therefore, we limit the growing degree days to the upper tail of the distribution where all values are greater than two standard deviations from the mean of the distributions.
Second, to calculate the expected gains from the networks by calculating a difference-in-difference variable. First, we calculate the difference between farmer’s expected gain from the network and their expected gains as if they were not part of the network. Then, we calculate the same difference under various climate change scenarios. Lastly, we calculate the gap between the two calculated differences. This gap captures the farmer’s potential gain from the small network under each climate change scenario.

Firstly, we adjust step C.2.1.1 by defining three new distributions for the Growing Degree Days, each with the mean shifted by 10%, 20%, and 30% respectively. Subsequently, we focus solely on the extreme values of these distributions. This entails limiting the growing degree days to the upper tail of the distribution, where all values surpass two standard deviations from the mean of the distributions.

Secondly, we modify the step C.2.1.6 to compute the expected gains from the networks, we define a difference-in-difference variable. Initially, we calculate the gap between a farmer’s expected gain from the network and their expected gains if they were not part of the network. Then, we repeat this calculation under various climate change scenarios. Finally, we determine the gap between the two calculated differences. The calculated gap captures the potential gain for farmers from the small network under each climate change scenario.

The rest of the simulations remain unchanged from the instructions outlined in step C.2.1.

C.3 Simulating the Value of Learning from Farmer’s Expanded Network

In this part, there are only two changes from section C.2 of this appendix:

C.3.1 First, we expand the farmer’s network by adding 5 new neighbors for each farm in our baseline network. The new neighbors are added randomly within a 25-mile radius. Using our data prepared in section C.1 of this appendix, first, we randomly select five neighbors located within 25 miles of each farm. Then we assign a unique identifier for those farms and using ArcGIS we connect those new neighbors to the network.

C.3.2 Number of iteration: Second, we modify the step C.2.1 of the previous section of appendix C by changing the number of simulations to 4001. The rest of the simulations remain unchanged. We follow exactly the same process as detailed in C.2.1.1 through C.2.1.6.

We maintain the steps for simulating climate change scenarios unchanged from the previous instructions outlined in step C.2.2.

C.4 Simulating the Value of Learning from Farmer’s Expanded Network with Signal Selection

In this part of the simulation, we introduce criteria for signal senders. We assume that farmers receive signals from the 10 nearest neighbors. This condition eliminates noisy signals from farms located in far locations and improves the geographical relevance of the signals.

In this part of the simulations, there are two deviations from the previous section C.3 of the appendix C:

C.4.1 First, restrict the signal-sending farmers to be the only ten nearest farmers. The average distance for the signal-sending farm here is 6.8 miles with a minimum of approximately 0 miles and a maximum of approximately 44 miles.

In our pool of signal-receiving farmers for the expanded network, we have 595 farms and each receives 10 signals from their nearest neighbors.

C.4.2 Number of iteration: We set the number of simulations to 4001. Then, we create a loop to iterate through the following steps to simulate the value of the network. To summarize our results on the graphs, we use different numbers of simulations to have a similar frequency on the y-axis of the graphs. Since the number of observations for our sub-samples varies when we limit our simulation for high and low-precision signals, then we change the number of simulations for the low-precision sub-samples to get a similar number of observations.

The other steps for simulating the value of learning from the network and the calculations under different climate change scenarios remain exactly the same as before.
Appendix D - Additional Simulation Results

Distribution of Gains for the Expanded SIRAC Network

Figure 5: Simulation of Farmer’s Expected Gains by Signal Precision - Expanded Network

Note: Figure 5 shows the distribution of farmer’s expected gain from learning from scouting and from the network for the expanded SIRAC network with an application to management of ECB pest. Farmers have three channels of learning: previous knowledge, scouting, and network. The blue histograms plot the distribution of farmer’s gain from scouting relative to the reference case of only previous knowledge. The orange histograms plot the distribution of farmer’s gain from scouting and networking relative to the case of only previous knowledge. The difference between the orange and blue histograms captures the gain from the network. The dashed vertical line represents the median value of each distribution. Each graph plots distributions for different precision levels of the signals from scouting and from the network.
### Descriptive Statistics - Results

Table D.1: Descriptive Statistics - SIRAC Network

<table>
<thead>
<tr>
<th>Variable</th>
<th>obs</th>
<th>P10</th>
<th>mean</th>
<th>St.dev</th>
<th>P90</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal Precision</td>
<td>4.76e6</td>
<td>0.43</td>
<td>0.59</td>
<td>0.13</td>
<td>0.85</td>
<td>0.29</td>
<td>1.00</td>
</tr>
<tr>
<td>Scouting Precision</td>
<td>4.76e6</td>
<td>0.57</td>
<td>0.59</td>
<td>0.12</td>
<td>0.86</td>
<td>0.14</td>
<td>1.00</td>
</tr>
<tr>
<td>Initial pest population</td>
<td>4.76e6</td>
<td>1.36</td>
<td>2.00</td>
<td>0.50</td>
<td>2.65</td>
<td>0.00</td>
<td>4.00</td>
</tr>
<tr>
<td>Pest Carrying Capacity</td>
<td>4.76e6</td>
<td>21.36</td>
<td>22.00</td>
<td>0.50</td>
<td>22.65</td>
<td>19.86</td>
<td>24.15</td>
</tr>
<tr>
<td>GDDs</td>
<td>4.76e6</td>
<td>1562</td>
<td>1900</td>
<td>302</td>
<td>2325</td>
<td>1500</td>
<td>3706</td>
</tr>
<tr>
<td>Distance (miles)</td>
<td>4.76e6</td>
<td>20.76</td>
<td>112.38</td>
<td>63.64</td>
<td>192.91</td>
<td>0.38</td>
<td>266.78</td>
</tr>
<tr>
<td>Corn Price</td>
<td>4.76e6</td>
<td>5.33</td>
<td>6.40</td>
<td>0.83</td>
<td>7.46</td>
<td>3.15</td>
<td>10.04</td>
</tr>
<tr>
<td>Average yield per acre</td>
<td>4.76e6</td>
<td>166.55</td>
<td>172.99</td>
<td>5.01</td>
<td>179.39</td>
<td>152.44</td>
<td>193.53</td>
</tr>
<tr>
<td>Expected Gain</td>
<td>4.76e6</td>
<td>$130</td>
<td>$298</td>
<td>$148</td>
<td>$494</td>
<td>0</td>
<td>$635</td>
</tr>
</tbody>
</table>

Table D.1 summarizes the descriptive statistics of the parameters in our simulation model for the SIRAC network and the farmer’s expected gain from the network, assuming that they receive ten signals from the network.
Table D.2: Descriptive Statistics - Expanded Network

<table>
<thead>
<tr>
<th>Variable</th>
<th>obs</th>
<th>P10</th>
<th>mean</th>
<th>St.dev</th>
<th>P90</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal Precision</td>
<td>$23.8 \times 10^7$</td>
<td>0.42</td>
<td>0.61</td>
<td>0.20</td>
<td>0.89</td>
<td>0.43</td>
<td>1.00</td>
</tr>
<tr>
<td>Scouting Precision</td>
<td>$23.8 \times 10^7$</td>
<td>0.57</td>
<td>0.75</td>
<td>0.17</td>
<td>0.93</td>
<td>0.14</td>
<td>1.00</td>
</tr>
<tr>
<td>Initial pest population</td>
<td>$23.8 \times 10^7$</td>
<td>1.36</td>
<td>2.00</td>
<td>0.50</td>
<td>2.61</td>
<td>0.11</td>
<td>3.94</td>
</tr>
<tr>
<td>Pest Carrying Capacity</td>
<td>$23.8 \times 10^7$</td>
<td>21.36</td>
<td>22.00</td>
<td>0.51</td>
<td>22.65</td>
<td>20.3</td>
<td>23.79</td>
</tr>
<tr>
<td>GDDs</td>
<td>$23.8 \times 10^7$</td>
<td>1564</td>
<td>1903</td>
<td>301</td>
<td>2330</td>
<td>1500</td>
<td>3473</td>
</tr>
<tr>
<td>Distance (miles)</td>
<td>$23.8 \times 10^7$</td>
<td>20.18</td>
<td>94.05</td>
<td>53.09</td>
<td>162.38</td>
<td>0.00</td>
<td>245.36</td>
</tr>
<tr>
<td>Corn Price</td>
<td>$23.8 \times 10^7$</td>
<td>5.32</td>
<td>6.40</td>
<td>0.84</td>
<td>7.47</td>
<td>3.34</td>
<td>9.30</td>
</tr>
<tr>
<td>Average yield per acre</td>
<td>$23.8 \times 10^7$</td>
<td>166.63</td>
<td>172.97</td>
<td>5.03</td>
<td>179.47</td>
<td>156.79</td>
<td>192.07</td>
</tr>
<tr>
<td>Expected Gain</td>
<td>$23.8 \times 10^7$</td>
<td>$149$</td>
<td>$348$</td>
<td>$171$</td>
<td>$576$</td>
<td>$9$</td>
<td>$649$</td>
</tr>
</tbody>
</table>

Table D.2 summarizes the descriptive statistics of the parameters in our simulation model for the expanded network and the farmer’s expected gain from the network, assuming that they receive ten signals from the network.
Table D.3: Descriptive Statistics - Expanded Network with Signal Selection

<table>
<thead>
<tr>
<th>Variable</th>
<th>obs</th>
<th>P10</th>
<th>mean</th>
<th>St.dev</th>
<th>P90</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal Precision</td>
<td>47.6×10^6</td>
<td>0.86</td>
<td>0.98</td>
<td>0.05</td>
<td>1.00</td>
<td>0.71</td>
<td>1.00</td>
</tr>
<tr>
<td>Scouting Precision</td>
<td>47.6×10^6</td>
<td>0.57</td>
<td>0.75</td>
<td>0.17</td>
<td>1.00</td>
<td>0.14</td>
<td>1.00</td>
</tr>
<tr>
<td>Initial pest population</td>
<td>47.6×10^6</td>
<td>1.36</td>
<td>2.00</td>
<td>0.50</td>
<td>2.65</td>
<td>0.02</td>
<td>3.94</td>
</tr>
<tr>
<td>Pest Carrying Capacity</td>
<td>47.6×10^6</td>
<td>21.36</td>
<td>22.00</td>
<td>0.50</td>
<td>22.64</td>
<td>19.91</td>
<td>24.11</td>
</tr>
<tr>
<td>GDDs</td>
<td>47.6×10^6</td>
<td>2161</td>
<td>302</td>
<td>2324</td>
<td>1500</td>
<td>1561</td>
<td>3692</td>
</tr>
<tr>
<td>Distance (miles)</td>
<td>47.6×10^6</td>
<td>2.23</td>
<td>6.81</td>
<td>4.12</td>
<td>9.74</td>
<td>0.00</td>
<td>24.70</td>
</tr>
<tr>
<td>Corn Price</td>
<td>47.6×10^6</td>
<td>5.33</td>
<td>6.40</td>
<td>0.83</td>
<td>7.46</td>
<td>2.97</td>
<td>9.65</td>
</tr>
<tr>
<td>Average yield per acre</td>
<td>47.6×10^6</td>
<td>166.64</td>
<td>173.044</td>
<td>4.97</td>
<td>179.42</td>
<td>151.057</td>
<td>193.49</td>
</tr>
<tr>
<td>Expected Gain</td>
<td>47.6×10^6</td>
<td>$223</td>
<td>$431</td>
<td>$188</td>
<td>$677</td>
<td>$5</td>
<td>$835</td>
</tr>
</tbody>
</table>

Table D.3 summarizes the descriptive statistics of the parameters in our simulation model for the expanded network with signal selection and the farmer’s expected gain from the network, assuming that they receive 10 signals from the network.
Distribution of the Network Climate Adaptation Values for the SIRAC Network

Note: Figure 6 illustrates the distribution of farmers' expected gains from both the SIRAC network and scouting activities under the scenario of a 10% increase in GDDs, specifically focusing on the management of European Corn Borer (ECB) pests. The blue histograms represent the distribution of differences in farmers' expected gains from scouting alone, comparing the scenario after a 10% increase in GDDs to the baseline scenario without climate change. Meanwhile, the orange histograms show the distribution of differences in farmers' expected gains from combining scouting and network signals, again comparing the post-10% GDD increase scenario to the no climate change baseline. The difference between the orange and blue histograms quantifies the network's adaptation value under the scenario of a 10% GDD increase. This difference highlights the additional benefit that network participation offers over scouting alone in adapting to climate change impacts. The dashed vertical lines in each graph mark the median value of the distributions. Each subgraph within Figure 6 shows distributions for various precision levels of scouting information and network signals.