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RESEARCH ARTICLE

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 $300 per acre in value against the impacts of extreme heat.[1]

Keywords: Climate change; Iowa; farmer networks; pest management; social learning

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

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; Jackson et al. 2011). Consequently, 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

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[1] Author Statements: We affirm that none of the authors of this manuscript have relevant material or financial interests in the research subject. There are no restrictions for sharing the data and code used for this manuscript. We can permanently share both the data and the code to replicate the results in the article.

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).

Optimizing the timing of pesticide applications is important not only for enhancing agricultural efficiency but also for reducing the environmental impacts associated with excessive pesticide use. Improper timing or over-application can result in pesticide runoff, which contaminates water bodies and negatively affects aquatic ecosystems (Schulz 2004; Stehle and Schulz 2015; Pimentel 2005; Damalas and Eleftherohorinos 2011). Additionally, pesticides can remain in the soil, disrupting non-target organisms, including beneficial insects, soil microbiota, and pollinators, all of which are essential for ecosystem health and crop production (Goulson et al. 2015; Chagnon et al. 2015; Sánchez-Bayo and Wyckhuys 2019). The volatilization of pesticides also contributes to air pollution and greenhouse gas emissions, worsening climate change (Bedos et al. 2002; Mostafalou and Abdollahi 2013). By optimizing the timing of pesticide applications, farmers may reduce their usage and minimize these environmental risks while still ensuring effective crop protection. This strategy aligns with the growing focus on sustainable agriculture, particularly in regions like Europe, where regulatory frameworks increasingly aim to reduce the ecological footprint of farming practices (European Commission: DG Health and Food Safety 2020).

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 adopt 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 which is 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 case study for a pilot farmer network in Iowa (SIRAC), consisting of 121 Iowa Soybean Association (ISA) farmers.[2] This network was established

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[2] The SIRAC network is a pilot project and does not represent a statistically representative sample of the broader population of farms in Iowa. Consequently, the simulated expected gains based on the SIRAC network should be interpreted as a case study analysis.

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. In contrast, 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 $68 to as high as $347 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 examine the economic benefits of expanding the network. The SIRAC network is extended by incorporating five neighboring farms located within a 30-mile radius of each current farm, resulting in a total of 605 farms in the network. Initially, this expansion yields only modest economic benefits without targeted signal selection. However, when we implement signal selection based on geographic proximity, the network's effectiveness improves significantly, decreasing the average distance for received signals by over 90% compared to the original SIRAC network. This targeted approach to signal dissemination leads to notable improvements in the economic benefits of network participation. With the new signal selection in place, the lowest quantile experiences gains of $109 per acre, representing an approximate 14% improvement compared to the expanded network without signal selection. For the highest quantile, the gains reach up to $518 per acre, indicating an approximate 38% increase relative to the expanded network's expected benefits. These results highlight the importance of signal selection in maximizing the value of network expansion for farmers.

Third, we investigate the network's adaptation value in extreme heat scenarios caused by climate change. Our findings reveal that the network provides significant benefits to farmers who are most vulnerable to pest infestations. Specifically, the value of the network in mitigating the effects of extreme heat on pest populations exceeds $328 per acre at the 95th quantile of the distribution of network values in the extreme climate scenario, which involves a 30% increase in Growing Degree Days (GDD). In comparison, the median gain is $87 per acre for the same extreme scenario. The value of $328 represents approximately 37% of the average production cost per acre for corn producers in Iowa.[3]

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

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[3] According to Iowa State Extension services, the estimated cost of corn production in Iowa for 2025 ranges from $803.53 to $971.97 per acre, with a mid-range estimate of $881.03 per acre for a yield of 209 bushels per acre (see Iowa State Extension Estimated Production Costs).

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-Droesch (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.[4]

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[5]. 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. Rebaudo and 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.[6]

This article is structured as follows. Section 2 offers background information on the timing of pesticide applications and details the SIRAC network. Section 3 outlines an economic model of social learning specifically tailored to address pest management

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[4] Additionally, Beaman (2012) show how social connections can affect labor market outcomes, hinting at similar effects in agricultural productivity. Munshi (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, underscoring 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.

[5] Other studies, such as Miranowski (2016); Feder and Savastano (2006) and Hurley and Sun (2019), underscore the importance of learning from social networks.

[6] 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. Conversely, a lack of information can also lead to the underuse of 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.

challenges. In Section 4, we describe our simulation design, followed by Section 5, which presents the results of these simulations. Section 6 concludes the article and summarizes the policy implications derived from our findings. Additionally, Appendix A provides in-depth derivations of the economic model of social learning, Appendix B discusses the most prevalent pests affecting corn production, and Appendix C elaborates on the simulation methodology step-by-step. Lastly, Appendix D presents the results of the robustness check analysis, while Appendices E and F contain supplementary results.

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. Although these pests differ in their phenologies and environmental adaptability, agricultural extension services have identified three primary pest management strategies: planting transgenic corn varieties that express Bacillus thuringiensis (Bt) toxins; applying insecticidal seed treatments; and using soil or foliar insecticides (Hammond et al. 2014; Marlin Rice and Erin Hodgson 2017; Rice and Davis 2010).

The recent trend towards preemptive pest management strategies, particularly adopting Bt corn, marks a proactive approach to controlling pests. While Bt corn 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).

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 climatic conditions and farm management strategies, including crop rotation, field configuration, and seed selection. To navigate these challenges, farmers employ various 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 instance, guidance on managing the European Corn Borer (ECB) from the Iowa University Extension Services states:

"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 importance of synchronizing insecticide application with the pest's life cycle. Examples of pests that can be managed using pesticide applications are Corn Rootworm, Corn Earworm, Western Bean Cutworm, and the ECB (Bledsoe et al. 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) are designing and testing the Smart Integrated Farm Network for Rural Agricultural Communities (SIRAC), which is a connected farm network in Iowa[7]. 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 1a illustrates a simulated depiction of the SIRAC network across Iowa, with 121 farms. This simulated network was built using the 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 notably broad, starting from less than two feet at its minimum and extending up to approximately 278 miles at its maximum.

Figure 1 also illustrates the classification of pest detection technologies into "low" and "high" precision categories. This classification is based on the number of traps used in the fields, ranging from one to seven. Farms represented by red circles utilize more than four traps, indicating "high" precision and a higher ability to accurately detect pests. In contrast, gray circles represent farms with fewer than four traps, suggesting a less precise approach to pest detection. Based on the initial SIRAC network design, farms with more traps are better equipped to monitor pest activity, optimize pesticide application timing, and minimize crop damage.

To assess the advantages of expanding the SIRAC network, we simulate an enhanced version incorporating five additional neighboring farms within a 30-mile radius for each of the 121 existing farms, bringing the total to 605 farms. Figure 1b shows this expanded network in Iowa. The 30-mile radius threshold is informed by studies of the ECB movement patterns (Qureshi et al. 2005; Qureshi et al. 2006; Qureshi et al. 2006; Chiang 1961; Palmer et al. 1985). Research indicates that the dispersal of the European corn borer (ECB) is primarily localized, with most adults remaining within 300 to 359 meters (approximately 0.19 to 0.22 miles) of their release point. However, under favorable conditions, such as strong winds, they can travel long distances of up to 49 kilometers (30 miles). These instances of long-distance movement emphasize the importance of pest management strategies that consider the common short-range dispersal, as well as the less frequent but significant long-distance migrations. We assessed the reliability of our estimates for network gains at the 30-mile threshold by assigning zero weight to signals beyond 30, 40, and 50 miles and confirmed that the results remained consistent.

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

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[7] SIRAC website: https://sirac.agron.iastate.edu/.

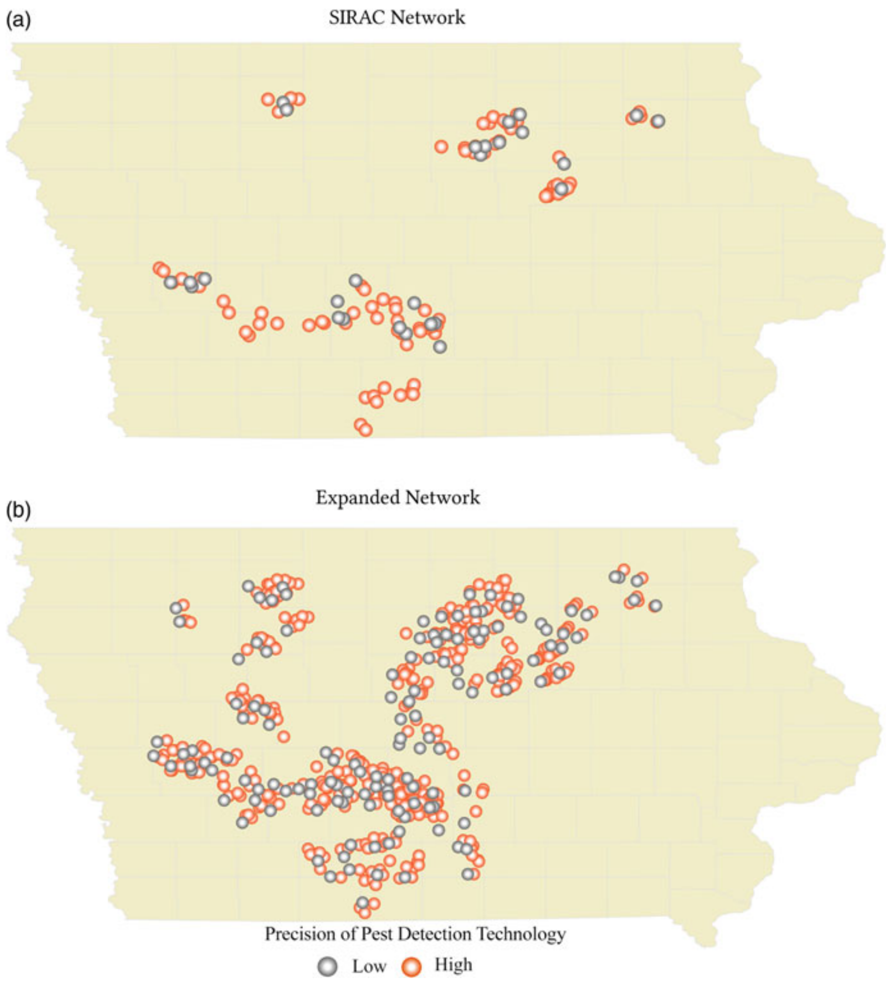

Figure 1. Farmers' network: panel (a) displays the SIRAC Network with 121 farmers located in Iowa; panel (b) shows our hypothetical expanded network with 605 farmers.

economic model, originally developed by Rosenzweig and 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 BenYishay and Mobarak (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 as $\tilde{\tau}_{it}$, which we decompose into two components: (*a*) the universal optimal timing across farms, represented by τ^*; and, (b) a farm and season-specific term, μ_{it}. We posit that μ_{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 ϑ_μ^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.

$$\tilde{\tau}_{it} = \tau^* + \mu_{it} \tag{1}$$

Extension agencies and pesticide suppliers offer guidance on τ^*, the recommended timing for pesticide application within a specific region. However, μ_{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 μ_{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 μ_{it}.

Pest Population: Farmers assess the pest population on their farms to determine the optimal timing for pesticide application. This evaluation serves as a learning exercise, allowing them to understand pest population dynamics better. To facilitate this understanding, we incorporate a straightforward model of pest population growth within the target-input framework. The pest population dynamics follow a simplified logistic pest growth equation, a mathematical model that illustrates how a pest population changes over time while considering carrying capacity, which is the maximum population size that the environment can sustain. The growth rate of the population is expressed by the following differential equation:

$$\frac{dP_t(GDD)}{dGDD} = r(GDD)P_t(GDD)\left(1 - \frac{P_t(GDD)}{K}\right). \tag{2}$$

In this equation, $P_t(GDD)$ denotes the pest population size at time t, K indicates the carrying capacity, and $r(GDD)$ represents the temperature-dependent intrinsic growth rate, which changes based on the accumulated degree days, GDD. Growing Degree Days (GDD) is a cumulative measure of heat accumulation over time, commonly used that predicts the development rates of temperature-dependent organisms (Stevenson et al. 2008; Rice and Davis 2010; Kocmánková et al. 2011; Marlin Rice and Erin Hodgson 2017).[8] This pest population model is particularly useful in agricultural and ecological studies because it captures the initial exponential growth of a population followed by a slowdown as resources become limited.[9] The term $\left(1 - \frac{P_t(GDD)}{K}\right)$ imposes a density-dependent constraint, ensuring that the growth rate diminishes as the population size nears its environmental limit, K.

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[8] The pest's population function is a solution to the differential equation (2), where: $P_t(GDD) = \frac{K}{1+\left(\frac{K-P_0}{P_0}\right)e^{-r(GDD)t}}$. Here, P_0 represents the initial pest population size at time $t = 0$. For more details regarding the pest population dynamics, see Appendix A.

[9] This model is a well-established insect and pest population framework commonly used in population growth studies (Berryman 1999; Régnière et al. 2012; Huseth and Groves 2013; Kocmánková et al. 2011; Robinet et al. 2012; Meinke et al. 2009; Rabajante et al. 2019), which depends on the accumulated growing degree days from the initial spring emergence of adult moths and the carrying capacity, provide insights into the functional form and parameters of the pest population, particularly the relationship between accumulated *GDDs* and the pest population growth outcomes. Biological and bacterial population studies, mathematical ecology, and pest management in insect biology have extensively employed the time-dependent logistic growth function with environmental constraints. Key references include Lobo and Acosta

Researchers have modified the logistic growth equation to incorporate growing degree days in pest management. This model transitions from a time-based framework to one that relies on thermal time by substituting time with accumulated growing degree days. This adjustment improves the accuracy of predictions concerning pest population dynamics in relation to temperature variations (Robinet et al. 2012; Meinke et al. 2009). This approach is commonly employed for forecasting pest outbreaks, optimizing control measures, and assessing the impacts of climate change on pest behavior and population trends (Rabajante et al. 2019; Kocmánková et al. 2011; Marlin Rice and Erin Hodgson 2017; Robinet et al. 2012). It has been specifically utilized to enhance predictions of population changes in the ECB over time (Ivezić et al. 2023).[10]

To address the uncertainty in pest population estimates, we define $P_t(GDD)$ as a random variable following a normal distribution, with mean $\mu_{P_t(GDD)}$ and variance $\vartheta^2_{P_t(GDD)}$. As farmers monitor their fields, they gather more accurate information about $\mu_{P_t(GDD)}$, which helps them make better predictions about future pest populations and reduces the variability of these predictions as the season progresses. We use the pest population predicted from equation 2 to calculate the yield penalty factor in the farmer's profit function.

Yield Penalty: The yield penalty is the percentage reduction in corn yields resulting from the increase in pest population. We follow the studies of Hazzard (2021) and Dean and Hodgson (2018) to determine the yield loss attributed to ECB larvae. According to these studies, the anticipated yield loss is directly tied to the number of ECB larvae present per plant and the accumulated growing degree days. Notably, significant ECB population emergence is estimated to occur after approximately 375 GDDs, with peak population levels identified around 1192 GDDs, followed by a reduction in activity past 1500 GDDs as the ECP reaches its carrying capacity. Each larvae per plant is anticipated to result in a yield loss of about 5%, implying that if the pest reaches its carrying capacity K larvae per plant, it could lead to total crop loss.

We define the yield penalty as:

$$L(P_t(GDD), K) = \frac{P_t(GDD)}{K} \times 100 \qquad if \quad P_t(GDD) < K, \qquad 100 \quad otherwise \tag{3}$$

The yield penalty can be estimated by the ratio of the pest population size per plant to the carrying capacity for that pest. For the ECB, the carrying capacity is 22 larvae per plant. Each additional larva corresponds to an approximate 5% reduction in yield, aligning with findings from Hazzard (2021) and Dean and Hodgson (2018). As the pest population approaches the carrying capacity K per plant, the risk of total yield loss significantly increases. The yield penalty can range from 0% to 100%. A value of 0% occurs when GDD are below the minimum threshold, making the climate unsuitable for pest development, resulting in zero larvae per plant. As GDD increases, the pest population grows, and the yield penalty rises.

Farmer's Production Function: The production function in the target-input model is crucial for understanding how optimal timing in pest management affects corn yield. It is defined as follows:

(1995); Lactin et al. (1995); Kot (2001); Murray (2002); Shao et al. (2017); Wang and Dwyer (2007); Damos and Savopoulou-Soultani (2012); Tjorve and Tjorve (2017).

[10] We determined the range for growing degree days based on studies linking ECB populations to yield loss ((Hazzard 2021; Dean and Hodgson 2018) and Ivezić et al. (2023)). These studies show that larval population growth is closely tied to GDD accumulation, starting with the first moth emergence in spring. Population growth typically begins around 375 GDD, peaks near 1192 GDD, and declines beyond 1500 GDD as it nears carrying capacity.

$$q_i(\tau_i) = \bar{q}_i\left[1 - L(P_t(GDD), K)(\tau_i - \tilde{\tau}_i)^2\right] \tag{4}$$

In this equation, $q_i(\tau_i)$ denotes the corn yield per acre on farm i, while $\bar{q}_i$ represents the maximum potential yield achievable when pesticides are applied at the optimal time, denoted as $\tilde{\tau}_i$. The expression $\bar{q}_i L(P_t(GDD), K)(\tau_i - \tilde{\tau}_i)^2$ quantifies the yield loss attributed to an increased pest population, which arises from deviations from this ideal application timing.

The quadratic formulation of the production function in the target input model can be understood as a local expansion around the optimal timing for pesticide application. This quadratic functional form is crucial for target input models because the expected value of the quadratic function provides an expression for farmers' profits in terms of the variances related to uncertain inputs. The symmetrical loss structure around the optimal timing illustrates the potential yield reductions resulting from premature applications, as well as losses from infestations caused by delayed applications. As deviations from the optimal timing increase, we anticipate that yield losses associated with significantly late applications will escalate. To simplify the notation, we omit other inputs from the production function, such as fertilizer and labor, but we do account for these inputs explicitly in the profit function.

Farmer Profitability: To understand how variations in the timing of pesticide application affect a farmer's expected profits, we analyze the farmer's profit maximization problem. A farmer, denoted as i, chooses the timing of pesticide application, $\tilde{\tau}_i$, and the number of scouting trips, S, with the goal of maximizing her expected profits, $E(\pi_i)$:

$$E(\pi_i) = \max_{\tau_i, s}\ p q_i(\tau_i) - s_i \times c_s - c_i \tag{5}$$

where p represents the price of corn; c_s is the average cost of scouting per acre; and c_i captures the average cost of applying pesticides and fertilizers, including labor costs. 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:

$$E\left(\pi_i^*\right) = p\bar{q}_i\left[1 - L(P_t(GDD), K)\left(\vartheta^2_{\tilde{\tau}_i} + \vartheta^2_{\mu}\right)\right] - s_i \times c_s - c_i \tag{6}$$

This equation links expected profitability directly to two types of variance. The first, $\vartheta^2_{\tilde{\tau}_i}$, 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, ϑ^2_{μ}, represents uncontrollable random effects, like specific weather events or unique pest developments, that learning processes cannot mitigate. Equation 6 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, $\vartheta^2_{\tilde{\tau}_i}$, highlighting the impact of both experiential learning and social learning on decision-making processes.

Cost Function and Lower Bound Interpretation: In our conceptual model, we assume that pesticide application costs remain constant regardless of when they are applied. This assumption aligns with standard agricultural practices in Iowa, where farmers typically apply pesticides at fixed rates based on their equipment specifications and field sizes. This approach ensures uniform coverage and operational efficiency, as pesticide application is often combined with other field operations, such as fertilization, using the same machinery and labor resources to minimize additional costs.

However, we also expand our conceptual model to account for situations where pesticide application costs, including labor, increase with later application timings. This adjustment considers scenarios where pest populations grow over time, necessitating more intensive pesticide use. To explore these cost dynamics, we include alternative functional forms in Appendix A. These include a linear cost function, which shows costs rising progressively over time; a quadratic cost function, capturing increasing marginal costs as pest infestations worsen; and a quadratic step cost function, which indicates that remedial costs sharply escalate after the optimal timing for pesticide application has passed.

Our results demonstrate that as pesticide application costs increase with delayed timing, the benefits of a farmer network also grow. This finding reinforces a broader interpretation of our estimated network gains as a lower bound, highlighting the robustness of our framework in scenarios where delayed pesticide application leads to higher intervention costs.

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 $\vartheta^2_{\tilde{\tau}_i}$ that incorporates learning by doing. We use the relationship between the optimal timing of pesticide application and the pest population to derive the variance $\vartheta^2_{\tilde{\tau}_i}$ conditional on an observation of the population $P_t(GDD)$.[11] Through Bayesian rule, we find:

$$\vartheta^2_{\tilde{\tau}_i} = \frac{1}{\rho_0 \quad + \quad \gamma \times \rho_S} \tag{7}$$

where ρ_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 ϑ_0^2 and higher ρ_0, thus reducing $\vartheta^2_{\tilde{\tau}_i}$ and enhancing profitability as shown in equation 6.

The second term in the denominator, ρ_S, reflects the precision of the farmer's learning technology, such as the accuracy of information obtained from scouting, inversely related to its variance (ϑ_S^2). High-quality scouting increases ρ_S. Investment in technologies like cameras and trapping devices can also increase the precision ρ_S. Finally, the precision of the learning technology is multiplied by a factor γ in equation 7 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 γ, 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.[12]

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[11] Appendix A details the derivation, resulting in the optimal timing's variance conditioned on $P_t(GDD)$ as $\tilde{\tau}_{i|P_t(GDD)} \sim N\left(\tau^{å}, \vartheta^2_\mu\left(1 - \rho_{\tau,p}\right)\right)$, where $\rho_{\tau,p}$ denotes the correlation between the optimal application timing $\tilde{\tau}$ and pest population $P_t(GDD)$.

[12] We derive in Appendix A an equation for γ using the Bayes rule. $\gamma = \frac{N}{\left[1 - \frac{\bar{q}_i L(P_t(GDD),K)}{\bar{q}_i L(P_t(GDD),K)+1} \rho^2_{\tau|P_0}\right]}$. γ is always positive given that the correlation between pest population and the timing of optimal pesticide application, $\rho^2_{\tau|P_0}$, is positive.

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, ρ_N, defined as the inverse of the variance of the optimal timing of pesticide application from the signal's sender, $\rho_N = \frac{1}{\vartheta^2_{\xi}+\vartheta^2_{\tau_j}}$, where and ξ represents an additional error term to account for the signal's noise. Our simulations introduce variability in signal precision based on the geographic proximity among farmers, aligning with methodologies commonly employed in learning literature (Conley 2001; Conley and Udry 2010).[13]

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 $\vartheta^2_{\tilde{\tau}_i}$ that incorporates social learning:

$$\vartheta^2_{\tilde{\tau}_i} = \frac{1}{\rho_0 \quad + \quad \gamma \times \rho_S + \quad N \times \rho_N} \tag{8}$$

This equation extends equation 7 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 ρ_N. This improvement in learning reduces the variance $\vartheta^2_{\tilde{\tau}_i}$, 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 6 defines this concept, which translates the impact of learning into monetary terms. As learning progresses, the variance $\vartheta^2_{\tilde{\tau}_i}$ 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 8. To quantify this value, Δ, we calculate

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[13] We also assume that signals from different farmers within a network are independent when applying Bayes updating. More specifically, we assume that $cov(\mu_i, \mu_j) = 0$ for any pair of farmers (i, j). The independence assumption would likely be violated in a large network of close farms or fields where signals of field i and field j received in the same week would be correlated. However, in networks such as the SIRAC network in our simulation, the minimum distance among farmers is less than 1 km. We could extend the model to incorporate correlation among signals explicitly but we leave this extension for future work.

the difference between the expected profit function incorporating social learning (via equation 8) and the expected profit absent social learning (via equation 7)[14]:

$$\begin{aligned}\Delta &= E(\pi_i^* | with \quad social \quad learning) - E(\pi_i^* | without \quad social \quad learning) \\ &= -pL(P_t(GDD), K)\bar{q}_i \left[\frac{1}{\rho_0 \quad + \quad \gamma \times \rho_S + \quad N \times \rho_N} - \frac{1}{\rho_0 \quad + \quad \gamma \times \rho_S} \right]\end{aligned} \tag{9}$$

We use equation 9 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.

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 9). 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 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,

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[14] Note that the learning effect defined in terms of expected profits captures a reduction in losses because of learning (see equation 6). The gain in profitability from social learning is therefore the negative of the difference in losses.

Table 1. Simulation parameters

Parameter	Values
Network Size	
SIRAC network	121 farmers
Expanded network	605 farmers
Farmer-Specific Parameters	
Initial precision of farmer's estimate	$\text{Uniform}(0, 1)$
Traps per farm (n_i)	$[1, 7]$
Scouting precision	$\frac{\text{Trapcount}}{\text{Maximumtraps}} = \frac{n_i}{7}$
Precision of signals	$\frac{1}{10}\sum_{i=1}^{10} signal_i \times w_i$
Signal Weight by Distance	
0 to 10 miles	1.00
10 to 25 miles	0.75
25 to 50 miles	0.50
More than 50 miles	0.25
Pest Population Dynamics	
Growth rate	$\frac{dP_t}{dGDD} = r(GDD)P_t\left(1 - \frac{P_t}{K}\right)$
Death rate (δ)	$\text{Uniform}(0, 0.4)$
Carrying capacity (K)	$\mathcal{N}(22, 0.5)$
Initial growth rate (r_0)	$\mathcal{N}(0.06, 0.02)$
Initial population (P_0)	$\mathcal{N}(2, 0.5)$
Corn Production Parameters ^{a}	$3^*\begin{bmatrix} P \\ Y \end{bmatrix}\mathcal{N}\left(\begin{bmatrix} \$4.89 \\ 132.89 \end{bmatrix}, \begin{bmatrix} 8.79 & -13.66 \\ -13.66 & 305.42 \end{bmatrix}\right)$
Corn Price (P) - \$/acre	
Corn Yield (Y)- $\frac{bu}{acre}$	
Scouting and Signals	
Frequency of scouting	10 per season
Number of signals received	10
Environmental Parameters	
Growing Degree Days (GDD) ^{b}	$\mathcal{N}(1500, 500)$
Simulation Settings	
Number of simulations	10,000

Note: Parameters were generated using 10,000 observations. Signal precision is based on trap counts and spatial weights. *a*) Corn price and yield are drawn from a multivariate normal distribution using historical data. *b*) GDD values are sampled from $\mathcal{N}(1500, 500)$ and truncated at 500 to reflect ECB pest dynamics, as values below 500 GDDs indicate no pest activity.

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 network. 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. 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.[15]

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. Additionally, the carrying capacity for pests, indicating the highest pest population that the agricultural ecosystem can sustain, is another essential

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[15] The 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 E.1, E.2, and E.3 in Appendix D offer descriptive statistics for the calculated signal precision for our different simulation models.

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 B-1 in Appendix B documents the impact of the ECB larvae, providing a detailed reference for the yield loss estimates related to ECB infestations.

Additional exogenous parameters include corn prices and the average corn yield, significantly impacting farmers' input decisions and profitability. In our simulations, we account for inflation, yield time trends, and the correlation between yields and prices to ensure accurate economic modeling. We model annual corn prices and yields as a bivariate normal distribution, incorporating their historical relationship based on USDA data from 1996 to 2023. To control for technological advancements, we adjust corn yields using an estimated exogenous growth rate of 1.15% per year, derived from existing agricultural studies. Similarly, corn prices are adjusted for inflation, using USDA's Crop Totals - Index for the Price Received. The resulting variance-covariance matrix captures the negative correlation between yield and price, reflecting the expected economic relationship where higher yields tend to lower prices. These adjustments ensure that our simulations provide a realistic representation of price and yield dynamics. Further details on these adjustments are provided in Appendix C.2.1.2.

Simulation of the SIRAC network and ECB pest management

In this section, we assess the economic value of a network in a more realistic setting for pest management[16]. We use the number of traps installed across 121 farms within the SIRAC network and the pairwise distances among these farms to determine the precision of scouting and 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. The precision calculation assumes that farm sizes within the SIRAC network are relatively homogeneous.[17] Next, we account for variations in the precision of signals received by farmers from their network peers. We consider both the scouting precision of the sending farm and the geographical distance to the receiving farm. 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.

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 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 distributions. We tailor these parameters – specifically the pest death rate, carrying

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[16] See Appendix F for the simulation of the network value for a theoretical baseline scenario with four simplifying assumptions. The baseline scenario illustrates the different components of the simulation.

[17] Due to confidentiality constraints, we cannot access the actual size of SIRAC farms. However, the farmer's technology capabilities determined the number of traps installed at each SIRAC farm during the project's pilot phase. So, there is no strong correlation between farm size and the number of traps in the pilot SIRAC network. Also, although there is variation in farm sizes in Iowa, the average size of acreage allocated to crops was 587 acres or 237 hectares (Iowa Extension Services). So, small variations in size would not significantly affect the estimates for scouting precision.

capacity, and initial population to the ECB based on empirical data and research findings detailed in the studies of Tyutyunov et al. (2008), Bledsoe et al. (2017), and Marlin Rice and Erin Hodgson (2017). Notably, we set the carrying capacity to 22 in the SIRAC simulation to accurately reflect the ECB's ecological reality and potential for the ECB pest population growth. 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 2 displays the expected gains for farmers in the SIRAC simulation. 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.

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. The overall trends for the SIRAC simulations highlight 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 2b and c illustrates).

We observe positive gains from network participation across the various scenarios examined. Specifically, using low-precision scouting technology, the expected gains from network participation are $135 per acre with low-precision network signals (Figure 2a) and $355 per acre with high-precision network signals (Figure 2b). When employing high-precision scouting technology, the benefits from network participation decrease but remain significant, yielding $232 for low-precision and $290 for high-precision network signals.

The SIRAC simulation reveals a significant spread in the distribution of gains from network participation, greater than the spread observed in a baseline simulation documented in Appendix E. We attribute this increased variability among farmers' gains to the considerable differences in the precision of scouting and network signals. Farmers who use advanced scouting technologies often benefit less from the network because their existing systems already provide them with high pest management efficiency. In contrast, farmers with less sophisticated scouting technology but access to more accurate signals – possibly due to their proximity to experienced farmers – tend to gain more from participating in the network. This variation in gains highlights how spatial and technological factors influence the value derived from the network. Understanding these dynamics can provide valuable insights for optimizing network design.

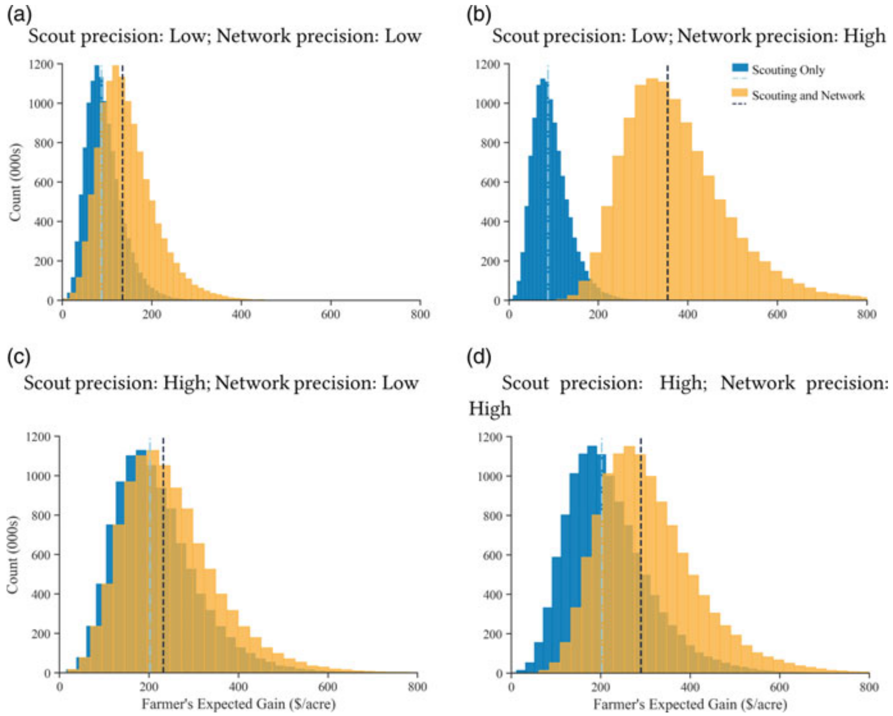

Figure 2. Simulation of farmer's expected gains by signal precision - SIRAC network. Note: Figure 2 shows the distribution of farmer's expected gain from learning from scouting and from the network for the SIRAC network with an application to management of ECB pest. Farmers have three channels of learning: 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.

The distribution of network gains

To identify which farms benefit most from network participation, we analyze the expected gains from network participation 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 2. 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 that the smallest expected gain from participation in the SIRAC network occurs at the 5th quantile, amounting to $68 per acre (see Panel A of Table 2). Farms that experience the least benefit from the network tend to be characterized by a greater distance from their peers, a lower accumulation of GDDs, and less precise network signals. These

Table 2. The farmer's expected gain from network participation

	Expected Gain from Network $ per acre (St. Dev)	Sender-Receiver Distance (miles)		GDD		Precision				Corn Price ($ per bushel)		Corn Yield (bushels per acre)	
						Network		Scouting					
	(1)	Avg. (2)	P10 (3)	Avg. (4)	P90 (5)	Avg. (6)	P90 (7)	Avg. (8)	P90 (9)	Avg. (10)	P90 (11)	Avg. (12)	P90 (13)
A. SIRAC Network													
Q5	68 (16)	130.59	48.18	1,819	2,184	0.38	0.56	0.56	0.57	3.81	5.61	137	162
Q25	130 (22)	129.50	42.63	1,851	2,234	0.46	0.62	0.57	0.57	4.56	6.20	134	157
Q50	210 (25)	118.25	18.37	1,873	2,276	0.47	0.64	0.58	0.57	4.73	6.39	133	156
Q75	298 (27)	104.80	11.28	1,889	2,298	0.50	0.65	0.60	0.86	4.97	6.51	132	155
Q95	347 (93)	97.23	9.31	1,987	2,447	0.55	0.70	0.61	0.86	5.46	6.92	132	153
B. Expanded Network													
Q5	96 (18)	117.73	52.85	1,825	2,193	0.23	0.21	0.38	0.35	3.90	5.62	137	161
Q25	154 (11)	116.09	47.13	1,852	2,237	0.33	0.92	0.50	0.91	4.49	6.17	134	157
Q50	254 (26)	111.92	36.69	1,866	2,263	0.56	1.00	0.65	0.91	4.68	6.33	133	155
Q75	318 (23)	108.51	31.98	1,891	2,301	0.72	1.00	0.69	0.91	5.01	6.53	132	154
Q95	376 (94)	106.10	28.12	2,047	2,507	0.84	1.00	0.68	0.91	5.40	6.86	131	153
C. Expanded Network with Signal Selection													
Q5	109 (21)	7.10	2.11	1,809	2,159	0.96	1.00	0.76	1.00	4.25	5.51	139	162
Q25	186 (24)	7.01	2.10	1,821	2,228	0.96	1.00	0.76	1.00	4.27	6.18	139	161
Q50	312 (31)	6.95	2.11	1,848	2,247	0.97	1.00	0.75	1.00	4.43	6.25	138	160
Q75	356 (42)	6.86	2.09	1,898	2,311	0.97	1.00	0.76	1.00	4.54	6.52	138	158
Q95	518 (90)	6.73	2.09	2,030	2,464	0.97	1.00	0.75	1.00	4.55	6.65	138	155

Note: Panel A summarizes the farmer's expected gains from participating in the SIRAC network for European Corn Borer (ECB) pest management. Panel B presents the gains for the expanded network, while Panel C reports the gains for the expanded network with signal selection. The table includes averages, standard deviations, and tail values at the 10^{th} percentile (P10) and the 90^{th} percentile (P90).

farms also generally have lower average corn prices and yields, and their scouting technology has slightly lower precision compared to farms at higher quantiles: 0.56 at the 5th quantile compared to 0.61 at the 95th. As a result, they are initially less vulnerable to pest infestations and still have the capacity to gather and learn from their scouting data. However, the pest management information they receive from their peers tends to be less accurate, further diminishing the value of network participation for these farmers.

Conversely, the highest gain from participation in the SIRAC network is $347 per acre, observed at the 95th quantile. Farmers in this high quantile are more susceptible to pest infestations due to a higher accumulation of GDDs and benefit from the highest corn prices. Consequently, they face greater risks associated with ineffective pest management. Additionally, farmers at the 95th quantile exhibit slightly higher precision in their scouting efforts and receive the most accurate signals from the network, partly due to their proximity to other network members. Thus, while the farmers who gain the most from the network are at greater risk from external environmental and market conditions, they only have a slightly higher capacity to independently acquire optimal pest management knowledge.[18]

Network expansion

To assess the advantages of expanding the SIRAC network, we simulate an enhanced version incorporating five additional neighboring farms within a 30-mile radius for each of the 121 existing farms, bringing the total to 605 farms. The 30-mile radius threshold is informed by studies of the ECB movement patterns (Qureshi et al. 2005; Qureshi et al. 2006; Chiang 1961; Palmer et al. 1985). Research indicates that the dispersal of the European corn borer (ECB) is primarily localized, with most adults remaining within 300 to 359 meters (approximately 0.19 to 0.22 miles) of their release point. However, under favorable conditions, such as strong winds, they can travel long distances of up to 49 kilometers (30 miles). These instances of long-distance movement emphasize the importance of pest management strategies that consider the common short-range dispersal, as well as the less frequent but significant long-distance migrations. We assessed the reliability of our estimates for network gains at the 30-mile threshold by assigning zero weight to signals beyond 30, 40, and 50 miles and confirmed that the results remained consistent.

We also randomly assign a varying number of traps to each newly added farm, keeping the simulation parameters consistent with those used in the original SIRAC simulation. Figure 1 provides a map of 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 shows at least 8% increase in expected gains for farmers across all quantiles. This result highlights the positive impact that enhanced signal precision has in a larger network (see Table 2, Panel B, Column 2). Figure E1 in Appendix E illustrates the distribution of these gains for the expanded network.

This improvement in gains is due to the higher quality of signals about pest infestations, which come from closer neighbors. Such proximity allows farmers to refine their pest management strategies more effectively. However, the benefits of expanding the network to five times its original size are smaller than anticipated.

The main issue is the random selection of network signals. Even though more peer farmers are available, including some who are closer, the process does not prioritize signals based on geographical proximity between senders and receivers. As a result, farmers may still receive signals from peers located several hundred miles away. Without a better

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[18] We further investigated the distribution's tail by examining statistics for the 90^{th} 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, 9.31 miles away from their peers, have experienced 2,447 cumulative GDDs, and have received network signals that are more precise than those received by farmers at lower quantiles.

method for selecting signals, the modest gains from network expansion stem primarily from a slightly increased likelihood of receiving a more accurate signal.

To address this limitation, we will next simulate the expanded network by incorporating a mechanism for improved signal selection.

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.

With the introduction of signal selection based on geographic proximity, the average distance for received signals dramatically decreases by over 90%. Specifically, at the 95*th* quantile, the average distance for a signal in the expanded network, which stood at 106.10 miles without signal selection, decreases to 6.73 miles when implementing signal selection (as Panel C, Column 2 shows). This significant reduction in distance leads to a 16% increase in the precision of the network signal.

The impact of signal selection is particularly large at the lower quantiles. For example, at the 5*th* quantile, signal precision increases from 0.23 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.

Introducing signal selection significantly improved the benefits farmers gain from network participation. At the 5*th* quantile, gains rise from $96 per acre to $109 per acre, representing a nearly 14% increase. For the highest quantile, gains grow from $376 per acre to $518 per acre, a 38% improvement. Comparing the gains under the original SIRAC network to those with the expanded network and signal selection reveals even more substantial improvements – a 49% increase at the highest quantile and a 60% increase at the lowest quantile.

Robustness to alternative signal weighting criteria

Table D.1 in Appendix D presents a robustness check evaluating how different signal weighting criteria affect farmers' expected gains from the network, measured in dollars per acre. The analysis compares results across three models: SIRAC Network, Expanded Network, and Expanded Network with Signal Selection. The baseline model applies a weighting scheme based on distance, yielding average expected gains of $210, $254, and $312 per acre, respectively, for the three models. To assess robustness, alternative weighting approaches assign zero weight to signals beyond 30, 40, and 50 miles. The results remain highly consistent across these criteria, with only minor variations in expected gains, confirming that the model's findings are not highly sensitive to distance-based weighting. This supports the interpretation that the network benefits estimated in the study are robust and provide a lower bound on expected gains, particularly since the baseline approach already discounts distant signals. The robustness check also highlights that signal selection consistently enhances gains, reinforcing its role in optimizing network efficiency. Finally, Table D.2 in Appendix D extends the robustness analysis under a climate change scenario with a 10% increase in

GDDs. The findings indicate that network participation still delivers substantial expected gains, with the Expanded Network with Signal Selection yielding the highest returns.

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[19].

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; 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; 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[20].

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[21]. 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

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[19] The GDD exhibit both spatial and temporal variability across Iowa. For instance, according to the growing season map provided by Iowa State University - Iowa Environmental Mesonet, the GDD from the beginning of the growing season in 2024 to the corn harvest in mid-September ranges from 2610 GDD to 3354 GDD, with an average of 3023.13 GDD and a standard deviation of 225.07. In the mid-corn season (June 15, 2024), accumulated GDD values range from 871 GDD to 1298 GDD, resulting in an average of 1098.20 GDD and a standard deviation of 131.92.

[20] Ecology and management of ECB in Iowa field corn, Iowa State Extension, 2017: https://store.extension.iastate.edu/product/15141

[21] Percentage change in growing degree days 1948-2020. Source: https://www.epa.gov/climate-indicators/climate-change-indicators-growing-degree-days. Data source: NOAA, 2021. NOAA (National Oceanic and Atmospheric Administration). 2021. Global Historical Climatology Network Daily: Data access. https://www.ncei.noaa.gov/products/land-based-station/global-historical-climatology-network-daily. Accessed March 2021.

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[22]. 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 3 illustrates the outcomes of climate change simulations conducted for the expanded network, explicitly examining a scenario that anticipates a 10% rise in GDDs.[23] In this figure, the blue histograms represent the disparities in farmers' anticipated gains arising solely from scouting activities. This analysis contrasts the scenario with a 10% increase in GDDs against the baseline scenario, which assumes no climate change. In contrast, the orange histograms reflect the differences in expected gains for farmers when combining scouting efforts with network signals, following the same comparative approach between the post-10% GDDs increase scenario and the baseline where climate remains unchanged.

Graph A of Figure 3 shows the adaptation value of the expanded network under conditions of extreme GDDs, specifically when both scouting technology and network signal precision are 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 $52 per acre, or around 45% of the expected network gain under normal climatic conditions. This result shows that, even with low precision in learning mechanisms, the network still

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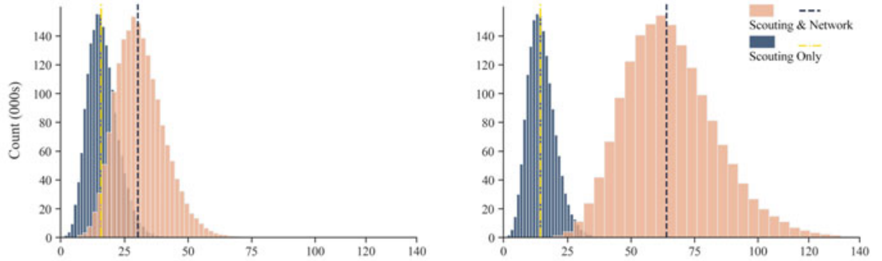
[22] Simulation results spanning the entire distribution of GDDs under the three climate change scenarios are available upon request from the authors.

[23] Appendix E details the simulation findings for the original SIRAC network.

(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

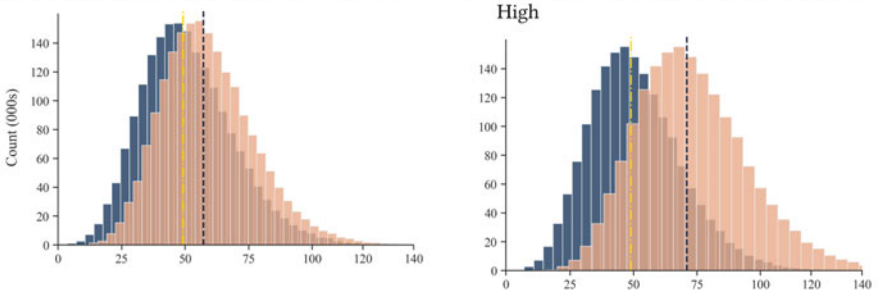


Figure 3. Simulation of the network climate change adaptation value - expanded network. Note: Figure 3 illustrates the distribution of farmers' expected gains for the expanded network under the scenario of a 10% increase in GDDs, specifically focusing on the management of ECB pests. The blue histograms 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% GDDs 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% GDDs 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 graph within Figure 3 shows distributions for various precision levels of scouting information and network signals.

offers significant value in scenarios characterized by extreme GDDs and a heightened risk of severe pest infestations.

Graph B of Figure 3 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 $62 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 $35 per acre, represents the value derived from investing in the improvement of network signal precision.

Graphs C and D from Figure 3 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 $10 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 $25 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 3 includes the corresponding GDDs 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 $16 to $38 per acre across the various climate change scenarios for the SIRAC network, as noted in Panel A of Table 3. In stark contrast, at the highest quantiles, the adaptation value for the scenario with a 10% increase in GDDs climbs to $108 per acre. This value further escalates to $126 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 GDDs. Other simulation parameters, 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 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.

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 $255 per acre (Panel C of Table 3). This improvement is particularly 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

Table 3. Network adaptation value for extreme heat scenarios

	GDD + 10%		GDD + 20%		GDD + 30%	
	Adaptation Value ($ per acre)	Extreme GDD	Adaptation Value ($ per acre)	Extreme GDD	Adaptation Value ($ per acre)	Extreme GDD
A. SIRAC Network						
Q5	16 (2)	2,773	35 (6)	2,886	38 (5)	3,044
Q25	26 (2)	2,769	56 (6)	2,931	61 (5)	3,067
Q50	63 (2)	2,813	74 (6)	2,953	78 (7)	3,100
Q75	84 (9)	2,917	95 (8)	3,061	101 (7)	3,154
Q95	108 (12)	3,065	124 (11)	3,109	126 (10)	3,195
B. Expanded Network						
Q5	17 (4)	2,743	38 (6)	2,879	43 (6)	3,012
Q25	29 (5)	2,785	65 (4)	2,935	68 6)	3,078
Q50	68 (4)	2,818	81 (5)	2,961	87 (5)	3,095
Q75	89(8)	2,905	98 (7)	3,062	106 (8)	3,198
Q95	111 (7)	3,089	132 (11)	3,180	141 (10)	3,312
C. Expanded Network with Signal Selection						
Q5	21 (3)	2,739	30 (2)	2,874	60 (4)	3,013
Q25	37 (2)	2,782	74 (6)	2,919	132 (4)	3,049
Q50	88 (4)	2,814	141 (6)	2,983	181 (7)	3,110
Q75	143(4)	2,878	210 (7)	3,013	280 (7)	3,172
Q95	178 (9)	3,106	255 (11)	3,215	328 (10)	3,445

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.

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 in varying degrees of severity of climate change. The adaptation value sees more significant increases as the 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 produce a proportional increase in adaptation value in the context of the base and expanded SIRAC network (panels A and B). In contrast, for the expanded network with signal selection (as shown in panel C), the increase in adaptation value from a severe to an extreme climate change scenario is comparable to the increase from moderate to severe. This pattern suggests that in the base network, there is a diminishing return on the adaptation value of network participation as climate change intensifies beyond certain ecological thresholds for pest growth. The results in panel C further highlight the benefit of signal selection, showing a more consistent increase in the adaptation value across the different climate scenarios.

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 $328 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 benefits of participating in the network vary significantly among farmers, suggesting the potential for differentiated pricing strategies. Some farmers may be willing to pay more for network access, while others might require subsidies. Simulations could help identify optimal pricing strategies. At this early stage of the SIRAC network pilot, the machine learning models, pest detection systems, and telecommunications technologies are still in the initial phases of development. Consequently, we do not yet have precise estimates of the costs associated with participating in the network. Early-stage costs for emerging technologies tend to be high but typically decline as the technology matures and the network expands. Instead of setting definitive cost expectations, our estimated network gains serve as a reference for network designers, helping them assess how much networking costs need to decrease for widespread farmer adoption.

The governance and coordination of a network like SIRAC could take various forms, allowing for flexibility in cost structures and accessibility:

1. Cooperative Model: The network could be organized as a cooperative, where farmers collectively share the benefits and costs of participation.

2. Industry Association Model: Similar to the Iowa Soybean Association, the network could be managed by an industry group, with farmers paying membership fees for access to the system.

3. Public Investment Model: Given the public benefits of reducing pesticide use – such as lower environmental pollution and improved water quality – the network could also receive government support through direct funding, subsidies, or public-private partnerships.

Strategic Network Expansion and Signal Selection: Our findings indicate that network expansion alone provides limited benefits unless combined with an effective signal selection mechanism. Implementing a strategic selection process – potentially based on geographical proximity, crop rotation patterns, climate conditions, soil attributes, or the accuracy of peer farmers' scouting technology – could significantly enhance the network's value. Even a basic selection criterion leads to substantial economic gains, underscoring the importance of carefully designing how signals are integrated into the network. Future simulations could further refine this approach by identifying which farms would benefit most from joining the network under these enhanced selection criteria, maximizing both economic efficiency and sustainability.

Complementary Role with Insurance: The network functions as an early warning system for pest infestations, which can enhance agricultural insurance policies. As climate change contributes to warmer growing seasons and increased pest risks, the network's capabilities in real-time data sharing, coordinated pest management, and adaptive farming practices can help reduce extreme yield losses. This, in turn, lowers risk exposure and decreases the frequency of insurance claims. Insurance companies could collaborate with farmer networks to encourage participation and gather aggregate information about anticipated yield losses.

Farmers who are part of the network can identify severe outbreaks earlier, enabling targeted interventions that minimize pest damage and reduce potential losses, thus lowering the likelihood of substantial insurance claims. Moreover, the aggregation of data within the network can enhance loss forecasting, allowing insurers to refine their actuarial models and decrease uncertainty, ultimately leading to lower premium rates.

To improve network effectiveness, it could be beneficial to incentivize farmers with high precision of scouting and more experience to participate, as their superior ability to detect pest outbreaks can improve the precision of network signals. One strategy to achieve this is to implement tailored premium rates based on the quality of data shared by farmers, which would encourage them to provide high-quality scouting information. In addition, insurance companies could design premium incentives that address data privacy concerns; for example, farmers who contribute valuable data might receive discounts on premiums or other benefits, alleviating concerns about data security.

Expanding the model to address multiple pests with distinct life cycles could amplify these advantages, as synchronized strategies across farms would further stabilize agricultural output and enhance financial resilience. By decreasing the probability and severity of extreme losses, farmer networks create a positive feedback loop that reduces individual farm risk as well as systemic risk for insurers. This can result in more affordable and sustainable insurance options for farmers.

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