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Agricultural Innovization: An Optimization-Driven solution for sustainable agricultural intensification in Michigan

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ABSTRACT

Humanity, now increasingly populous and affluent, poses a new challenge for the twentieth-first century farmer: increase food supply while maintaining the earth's underlying ecosystems. This paper proposes a novel systems approach, agricultural innovization, to sustainably increase food production. Innovization applies the knowledge obtained through multi-objective optimization to discover new agricultural management practices which reduce the risk of climate variabilities on crop yields. In agricultural innovization, an optimization platform generated the near-optimal management actions for 30 years using a calibrated crop model for maize. From those near-optimal solutions, recommendations for improving management practices were data mined. Then these improved recommended practices were evaluated over 420 validation seasons. The validation results were promising as the recommended practices obtained from the innovization increased yields and generated no negative change in nitrogen leaching. Furthermore, these recommendations can be applied to future seasons of management, which makes them a fully predictive application of multi-objective optimization.

1. Introduction

The current global agricultural production system struggles to meet food and nutrition security (El Bilali et al., 2019). This is primarily due to the 30% expected increase in world population by 2050, which will elevate food demand by 50% and require a 70% increase in food production (van Dijk et al., 2021). In addition, food accessibility will be further threatened by adverse climate conditions and volatile food prices, especially in developing and underdeveloped regions of the world (Richardson et al., 2018). Therefore, food production systems, being sensitive to abiotic and biotic shocks, need timely decisions in optimizing resource use. To mitigate these shocks, breeders have developed high yielding resistant crop cultivars. These modern cultivars require optimization of water and nutrient management to minimize yield gaps and to ensure the sustainability of agroecosystems (Tian et al., 2018). Despite being a critical resource in food production, water also faces scarcity due to population growth and climate change. The latest Intergovernmental Panel on Climate Change (IPCC) report highlights increased water-related food scarcity due to the increased frequency of droughts and poor water management (Arias et al., 2021).

Maize (Zea *mays* L.) is the third most important crop after rice and wheat, due its stable global productivity. This is primarily attributed to high-yielding seeds and modern management practices (Ricciardi et al., 2021). Despite continuous efforts in developing high yielding cultivars, many regions of the world are experiencing a stagnation in yield improvement over last two decades (Kucharik et al., 2020). One critical component of this stagnation is interannual variation in yield, which is primarily attributed to crop-climate feedback (Coffel et al., 2022; Kukal & Irmak, 2018). To address this variability in yield, a data-driven resource optimization approach is more feasible with the constrained resources availability (Eeswaran et al., 2021; Kropp et al., 2019). For example, in the United States Corn Belt, farmers were able to boost productivity over the last few decades by optimizing irrigation and nitrogen management (Jin et al., 2019; Wortmann et al., 2017; Zheng et al., 2019).

The traditional method of optimizing agricultural management practices is through field experiments, which are constrained by time and monitory resources (Vilayvong et al., 2015). However, computer

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modeling, monitoring, and optimization now allow farmers to optimize management practices at greater spatiotemporal scales (Abbasi et al., 2014; Tyagi, 2016). This is critical since managing or sustaining the agroecosystem under short, and long-term climatic variability requires a system approach with complex data handling (da Fonseca et al., 2020). Crop simulation models have been used to investigate the impact of management practices on crop growth and development (Araya et al., 2021; Jha et al., 2018). Additionally, data-driven simulation studies have developed novel methods of resource optimization for management practices at both farm (Kropp et al., 2019) and regional levels (Ban et al., 2019). These advancements are already paying off, considering that precision agriculture and information technology have significantly increased agricultural productivity (Ahmed et al., 2018; Basso, 2020; Monzon et al., 2018). However, system complexity and multi-dimensional data reduce optimization speed (Sabarina & Priya, 2015). In fact, it is impossible to exhaustively examine all management practices to find an optimum. However, optimization techniques efficiently find near-optimal solutions among all possible management practices. Classical optimization techniques, such as gradient descent (Curry, 1944) and linear programming (Chvatal, 1983), efficiently solve simple optimization problems, but perform poorly with more complex problems such as multi-modal, non-convex, and nonlinear problems (Deb, 2009). Agricultural optimization falls in the latter category, making it a good candidate for evolutionary optimization (Kropp et al., 2019). This study chose evolutionary optimization because it offers a less specialized but an overall more capable optimization than the classical techniques (Goldberg, 1989). Research has repeatedly demonstrated the efficacy of evolutionary algorithms in developing more optimal crop management practices (Akbari et al., 2018; Groot et al., 2012; Kropp et al., 2019; Mello Jr et al., 2013; Sarker & Ray, 2009).

In addition to evolutionary optimization, the utility of multi-objective (MO) optimization techniques has been widely examined for agriculture management. MO problems contain no single solution that simultaneously satisfies all objectives in the problem (Miettinen, 2012). For example, suppose a farmer aims to minimize irrigation while maximizing their yield. In that case, there are two equally optimal solutions: *Solution A* maximizes yield with considerable irrigation losses, and *Solution B* that minimizes irrigation by not irrigating at all. Each of these solutions is equally optimal, and no better solution exists that outperforms each solution in both categories at once. And between these two extreme solutions typically lie a group of solutions, known as a Pareto front, that are also equally optimal and offer different tradeoffs to the problem (Censor, 1977). In the above example, one solution may use a moderate amount of irrigation while attaining modest yields, which wastes less water than *Solution A* but gets higher yields than *Solution B.* Evolutionary multi-objective (EMO) optimization algorithms specialize in solving multi-objective problems with highly complex and irregular search spaces (Goldberg, 1989), which is why they were the method of choice in the study.

The primary difficulty in optimizing an agricultural system is predicting the weather (Jones et al., 2017). Without proper management, unpredictable meteorological events (e.g., precipitation, minimum air temperature, maximum air temperature, solar radiation) can either help the plant, kill the plant, or produce middling yields. One way to address these uncertainties is to widen the scope of optimization, since it is better to search innovations that are true for all possible weather patterns than to improve specific management actions for a given year. A data-driven approach to discovering such innovations entails data mining massive datasets of irrigation schedules to determine the defining characteristics of good management practices. Such datasets are hard to obtain through the traditional agronomic literature due to the time and costs required to run agronomic experiments (Vilayvong et al., 2015). However, the combination of crop models and optimization can produce such a dataset (Kropp et al., 2019; Saravi et al., 2021). Given a fixed weather pattern, MO algorithms can generate effective management practices for a given year (Kropp et al., 2019), which can then be data mined for their successful characteristics. This process, known as innovization, uses optimization results to mine data for new innovations in a given system (Deb & Srinivasan, 2006).

This study carefully examines weather patterns and their impacts on an agricultural system over 30 years to prescribe (i.e., innovize) new management actions that achieve sustainable intensification. Sustainable intensification is defined as increasing agricultural yields with no additional impact on environment or land use (Pretty and Bharucha 2014). This innovization procedure is novel because long-term optimization results are transformed into best practice recommendations without requiring new optimization for future climatic scenarios. Also, innovization has never before been applied to an agricultural application. This study hypothesizes that innovization will generate new knowledge of maize production within a given region. These data-driven innovations will then be translated to easy-to-understand management actions for regional farmers and weather patterns. In order to test these hypotheses, the following objectives were examined against the current best practices that are recommended by the local extension publications (herein called common practices): 1) evaluate the productivity and sustainability of long term innovization-based irrigation scheduling under the regional weather patterns; 2) gauge the productivity and sustainability of long term innovization-based fertilizer applications under regional weather patterns; and 3) gauge the productivity and sustainability of long term innovization-based coordinated irrigation and fertilizer management under regional weather patterns.

2. Materials and methods

2.1. Modeling overview

Overall, the innovization platform generates optimized management actions for the study site, compares them to management actions following common practices, and finally makes recommended amendments to the common practices accordingly (Fig. 1). We chose a study area with complete meteorological (1989–2018) and soil data to generate the optimized management actions and the management actions following common practices data (Sections 2.2). Using a calibrated crop model for the study site, an optimization platform generates the near-optimal management actions for the 30 years of weather data (Section 2.3 and 2.6) (Figure S2). Then, an algorithm representing farmers following common practices was established and ran with the same 30 years of weather data (Section 2.5). The 30 years of optimized and common practice management actions are then statistically compared (Section 2.6). Specifically, the analysis compares the amount of irrigation applied in each physiological growth stage and the timing of a second nitrogen fertilizer application during the growing season (Section 2.6). Finally, a validation routine measures the performance of the new amended practices and the original common practices to confirm or reject the efficacy of the innovization procedure. The validation is performed on 14 climatologically similar study sites around the primary study site (Figure S1).

2.2. Study area

The study area is a field in the village of Cassopolis within Cass County, Michigan, USA (42° 1′ 29.64′' N, 86° 10′ 15.6′' W) (Fig. 2). The location is in the humid temperate region of the Midwest USA Corn belt. The long-term (1989–2018) average, minimum, and maximum temperature of the location is 9.81 °C, 3.1 °C, and 16.6 °C, respectively, and the average annual precipitation is 1002.52 mm (Prism, 2015). About 60 percent of the annual rainfall occurs during the crop growing season of May-October. Although Michigan seems to have abundant freshwater resources, precipitation is low during critical crop growing summer months. Additionally, crops often suffer from water deficits during the peak growing season (Andresen et al., 2011). The major soil type is shallow sandy loam with moderate drainage.

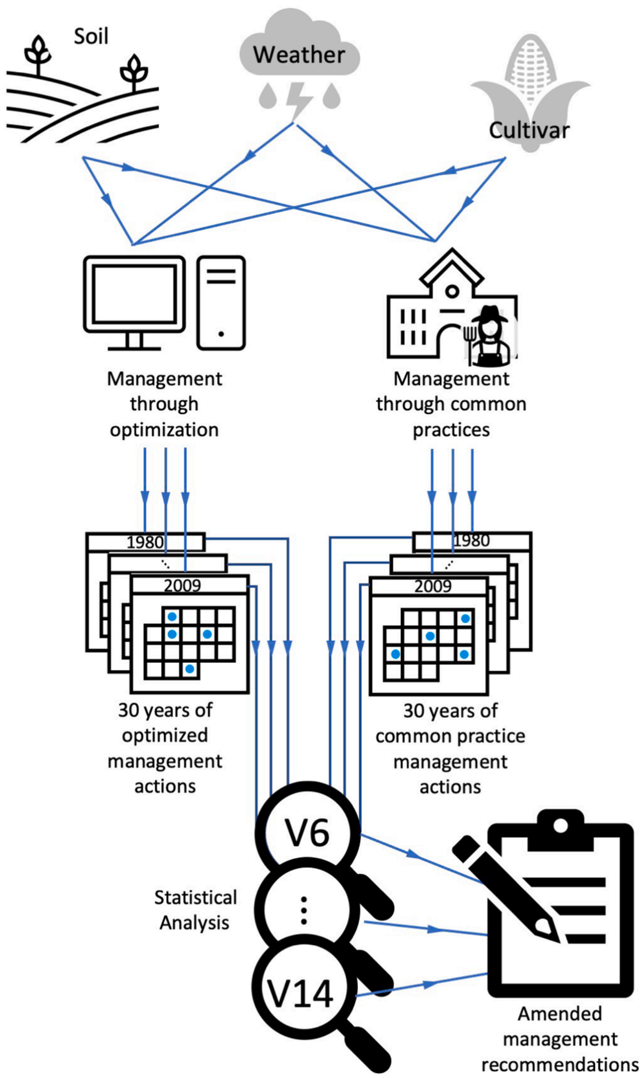

Fig. 1. Modeling overview.

2.3. Experiment setup

2.3.1. Crop model

This study employs crop simulation models to create the optimized management practices needed for innovization. The crop model selected for this study was the Decision Support System for Agrotechnology Transfer (DSSAT) version 4.7.5 (Hoogenboom et al., 2017; Jones et al., 2003). DSSAT is a collection of computer modules that are integrated to simulate crop growth for varying soil, weather, and genotype databases. DSSAT is also easily integrated into different modeling packages to consider climate variability and change (Han et al., 2017), remote sensing data (Li et al., 2015; Richetti et al., 2019), and advanced machine learning techniques (B. Singh et al., 2019). Its modules are reconfigurable and reusable, permitting users to modulate the code that connects the state and rate variables (de Abreu Resenes et al., 2019). These sets of capabilities make DSSAT a clear choice for this study.

2.3.2. Soil and weather data

Based on the soil type classification of the web soil survey webpage, the dominant soil for the study area was identified as sandy loam (NRCS, 2019). Sub-surface tile drain depth and spacing were kept at 75 cm and 10 m, respectively. Initial soil water content was held at 75% (0.145 cm^3/cm^3), based on soil sampling results from 2018 (Jha, 2019).

Daily weather data (i.e., solar radiation, maximum and minimum temperature, and rainfall) were obtained from Dowagiac, MI, the nearest Enviroweather station. Enviroweather is a weather station network developed and supported by Michigan State University (MSU Enviroweather, 2019). Since the weather station was established in 2014, historical weather data prior to 2014 (1989–2013) were collected from the Global Historical Climatology Network (GHCN) for Cassopolis to complete the 30-year climatological datasets (Menne et al., 2012). We used these daily weather data to calculate the growing degree days (GDD), a surrogate for crop phenological development. The Maize growing season is May through October.

2.4. Prediction of developmental stages based on growing degree days

Maize expresses a determinate growth habit with distinct vegetative and reproductive phases. Maize developmental stages are first based on vegetative development (V) and then on reproductive development (R). The most adopted method for determining vegetative stages is the Leaf Collar method (Ritchie et al., 1986) which can vary with hybrid, initial soil and planting conditions, and location. However, most of the Corn Belt hybrids produce 19–20 leaves. The appearance of consecutive

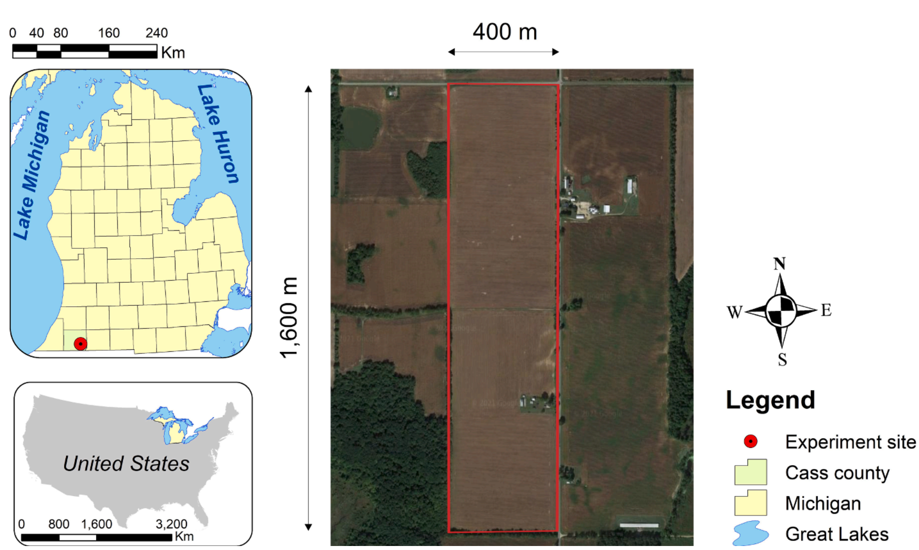

Fig. 2. Study Site.

leaves is driven by air temperature and hence can be predicted or tracked by estimating degree days or heat accumulation. The most recommended method of predicting heat accumulation is GDD, popularly known as 30/10 method (Abendroth et al., 2010). The optimal growing temperature for maize starts at 10° C and ends at 30 °C. Using 30-year historical weather data, we calculated the degree days (Equation (1)) in each year and estimated developmental stages.

$$GDD = \frac{T_{MIN} + T_{MAX}}{2} - 10 \tag{1}$$

where, GDD is growing degree day in Celsius, T_{MIN} is the minimum daily air temperature, and T_{MAX} is the maximum daily air temperature. Note that if temperatures are lower than 10° C, T_{MIN} is kept constant at 10° C, if temperatures are greater than 30 °C, T_{MAX} is kept constant at 30 °C.

Temperature based crop vegetative and reproductive development stages were used to optimize irrigation and nitrogen management strategies. Predicted stages based on air temperature can be seen in Table S1. These average values for each predicted stage and day were used in setting up the constants and constraints for optimization, including when to irrigate (30-year minimum of V6 through 30-year maximum of R2) and when to apply nitrogen (30-year minimum of V6 through 30-year maximum of V14) (Table 1).

All of the innovization years (1989–2018) were divided into dry, normal, and wet years of precipitation. Dry years are the driest 1/3 of the innovization years, wet years were the wettest 1/3 of the innovization years, and the final 1/3 were the normal years (Table S1). These categories were also used to characterize the precipitation for the validation scenarios (Table 1).

2.5. Common practice at the study site

Agronomic management of maize is primarily driven by specific developmental stages determined by the heat accumulation in plants (Abendroth et al., 2010). Growers in Cassopolis determine initial crop water requirement by measuring the accumulated soil moisture before the growing season. As the maize develops physiologically, growers irrigate after the midpoint of the vegetative stage (V6-V8) in addition to supplemental rainfall. Physiologically, crops need more water for biomass growth during critical growth stages, and hence this requirement is met through irrigation. Based on these growth stages and in order to optimize water use efficiency, farmers in Cassopolis generally plant on May 15. The irrigation source is groundwater pumping and the method is sprinkler irrigation. Under normal weather conditions, the common practice is to irrigate 10 mm after 50 days of planting (V6-V8 stage) at 5 days intervals up to the tasseling stage (60–70 days after planting (DAP)). For reproductive stages (i.e., from the tasseling stage onwards), growers irrigate 20 mm at 5 days intervals up to the R2 stage (i.e., blistering stage, or 100–110 DAP) (Fig. 3) (Kelley, 2016; Kelley & Hall, 2020; Kranz et al., 2008). In the case of heavy rainfall (i.e., greater than 20 mm), farmers typically wait ten days before resuming irrigation (Fig. 3). Similarly, nitrogen application time and amount are important to yield production and potential groundwater contamination. The common practice of applying nitrogen for Southwest Michigan's sandy to sandy loam soils is 200–210 Kg N/ha. This is based on the tool Maximum Return to Nitrogen (MRTN) recommendation, which growers adopt in the Corn Belt of the USA (Gramig et al., 2017). This application is split into two doses: pre-plant incorporation (75%) and another side-dressed dose (25%) between V6 and V14, depending on weather conditions. However, nitrogen requirement increases rapidly after the V8 growth stage (8-leaf collar stage), i.e., 55–60 DAP. The vigorous biomass growth during mid to late vegetative stages requires a large amount of nitrogen. Growers usually confine their side-dress application to V8-V10. Since rain negatively affects the application of nitrogen, the common practice is to delay the application until five days after heavy rainfall events (i.e., greater than 20 mm), three days after moderate rainfall events (i.e., greater than 10 mm), and two days after any other rainfall event (Fig. 4). These are the practices that this study aims to improve through the process of innovization.

Table 1
Optimization variables and constants.

Variables	
Parameter	**Differences between runs**
Weather	Different observed data for each year
Irrigation	When and how much to irrigate during the growing season between the 30-year minimum of V6 (DAP 46) and maximum start day of R2 (DAP 118)
Second nitrogen application	25% side dressed between the 30-year minimum of V6 and maximum of V14
Constants	
Parameter	**Constants across runs**
Planting date	May 15th
First nitrogen application	preplant incorporation 75% (of 200 kg)
Total nitrogen application	200 kg
Innovization period	1989–2018

2.6. Innovization framework

The first task in agricultural innovization is to generate many near-optimal irrigation and nitrogen schedules for a vast number of weather scenarios. These schedules are ideally generated using numerous optimizations runs over the entire span of potential weather conditions; a wide breadth of initial conditions ensures that we are analyzing the widest range of possible meteorological scenarios. The agronomical literature recommends 30 years of weather representative to better understand the cropping systems (Deshcherevskaya et al., 2013). Therefore, from 1989 to 2018, 30 independent optimization runs improved the common management practices (i.e., irrigation and nitrogen applications) for each growing season.

All MO runs optimized three objectives: maximizing maize yield, minimizing water usage, and minimizing nutrient leaching. The decision variables (i.e., the management practices to optimize) included when and how much to irrigate during the growing season, and when to apply the second nitrogen application (Table 1). The first nitrogen application, 150 kg/ha at DAP 0, remains constant throughout all scenarios (Table 1). Formally, the optimization is defined by:

$$\begin{aligned} &\max f_Y(i_{46}, \cdots, i_{118}, N) \\ &\min f_I(i_{46}, \cdots, i_{118}, N) \\ &\min f_L(i_{46}, \cdots, i_{118}, N) \end{aligned} \tag{2}$$

where, i_{46} represents the 30-year minimum start date of V6 (DAP 46), i_{118} represents the 30-year maximum end date of R1 (DAP 118), and I is the entire irrigation schedule ($I = \{i_{46}, \cdots, i_{118}\}$). In other words, each $i_d \in I$ represents the amount of irrigation for day-after-planting d in the irrigation schedule. The total irrigation applied on DAP i is between 0 and 30 mm ($i \in [0, 30]$). N, which represents the date of the second nitrogen application, falls between the minimum V6 and the maximum V14 ($N \in [\min(\text{V6}), \max(\text{V14})]$) for the 30 years of study (Table S1) and involves applying 50 kg/ha of nitrogen. f_Y, f_I, and f_L are yield, total irrigation usage, and total nitrogen leached into the soil, respectively. Each of these objectives is a function of the irrigation schedule and nitrogen application variables, as well as the fixed soil, weather, and cultivar for each year. DSSAT provides the total irrigation, yield, and leaching (f_I, f_Y, and f_L) by simulating maize growth for the given soil conditions, cultivar genotype, weather, and management practices at the study site.

The EMO algorithm chosen for this study was the non-dominated sorted genetic algorithm III (NSGA-III), a powerful, many-objective

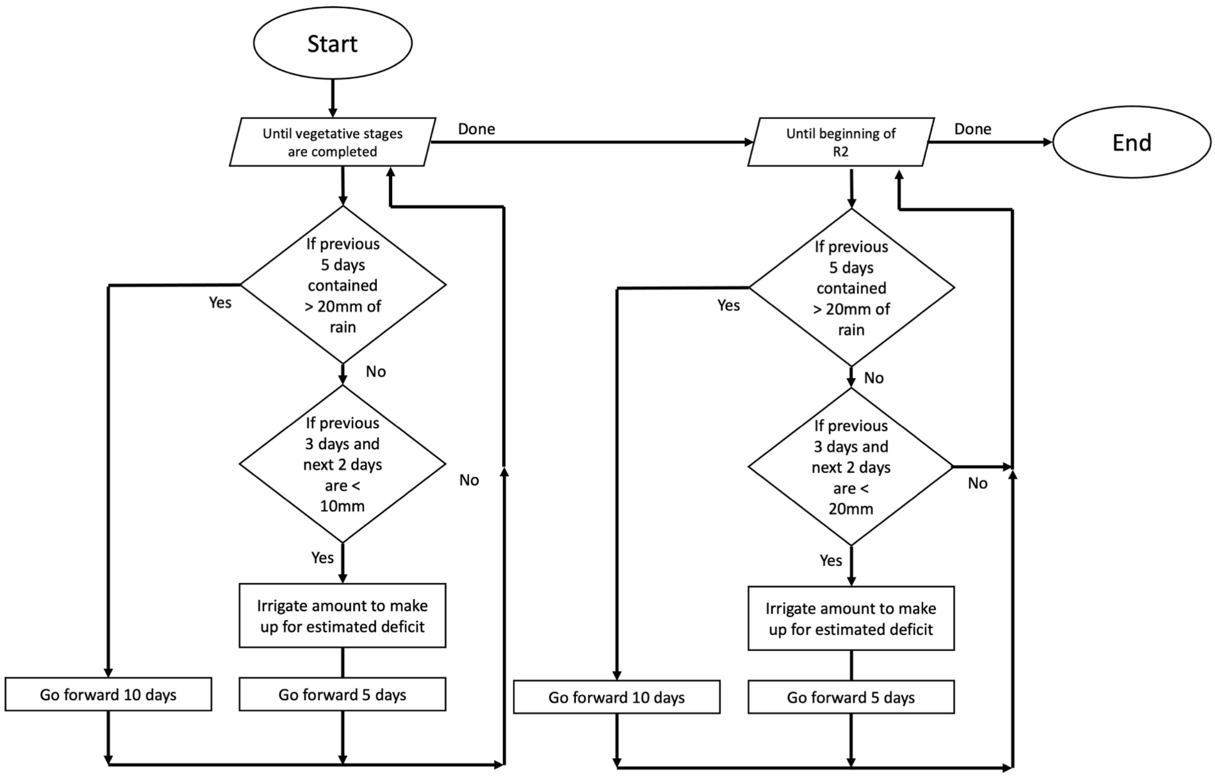

Fig. 3. Flow chart of common irrigation practices in Cass County, Michigan.

optimization algorithm that simultaneously prioritizes solution convergence and diversity (Deb & Jain, 2014). Because of the stochastic nature of EMO algorithms, the optimization was repeated 30 times for each year with different random seeds. Due to the long run time of the optimization in preliminary runs, thirty repetitions were determined to be the ideal balance between run time and sample size. This lowers the odds that a single optimization with poor convergence is included in the results.

Every irrigation solution ran during the optimization, regardless of fitness, was saved for analysis during the innovization. All solutions for 30 runs for a given year were then combined into a single set and sorted into non-dominated fronts (another term for a Pareto front). Non-dominated sorting takes all solutions from all 30 optimization runs and sorts them into Pareto fronts with increasing optimality. For example, the first front is globally optimal for the three objectives; the second front is globally optimal if the first front is removed, and so on.

Traditional optimization algorithms tend to struggle to optimize large-scale optimization problems. Luckily, expert knowledge of irrigation helps simplify the optimization procedure: irrigation schedules are known to be sparse (Kropp et al., 2019). In simpler terms, plants physiologically only need irrigation during a minority of days in the growing season. Formally, the optimal I is always a vector of values that are mostly zero. This class of problems are known as large-scale sparse multi-objective problems LSSMOP (Zille & Mostaghim, 2017). There are a several options to take advantage of this knowledge. Kropp et al. (2022) demonstrated that NSGA-II, a version of NSGA-III for lower objective spaces (Deb et al., 2002), solves sparse problems effectively with sparse population sampling (SPS). SPS consists of modifying the initial population of evolutionary algorithms to enforce a target sparsity, which starts the initial population off on advantageous footing during the first generation. The target sparsity for this study was set to 80%, or an irrigation schedule with 80% of days without irrigation based on the sparsity of common practice irrigation schedules in preliminary runs.

Once the 30 repetitions for the 30 years of optimization are completed, we are left with a large dataset of 489,614 unique irrigation schedules, their respective yields, leaching levels, and water usages. However, this dataset still poses a challenge to innovization: no attributes in the dataset are relevant to improving common practices (Fig. 3 and Fig. 4). Firstly, the raw attributes include the days of the growing season and how much irrigation was applied during those days, which is directly tied to the weather of that given year. Thus, the irrigation schedules must be first transformed into a weather-independent format. In addition, a raw irrigation schedule holds little meaning for a farmer in the study area and transforming the results into relevant attributes will simplify the results. Therefore, the optimization results were run through a process that transformed the raw irrigation schedules into what we will refer to as a knowledge attribute table. The knowledge attribute table includes the irrigation schedule transformed into variables that describe how much water is applied during each physiological stage. For example, one attribute describes how much irrigation water was applied during the V8 stage of growth. Transforming yearly optimal irrigation schedules into physiological terms standardizes the irrigation schedules across all weather patterns. In addition, it makes the data more understandable to farmers, who can easily determine the current physiological stage of a plant in the field. See the complete list of physiological attributes in Table 2. The final attributes are the threshold of heavy, moderate, and light rain rainfall in the context of nitrogen application. These values correspond to the common practices in the study site to delay the second nitrogen application by five days after heavy rainfall, three days after a moderate rainfall, and one day after light rainfall (Fig. 4). To determine the heavy rain threshold from raw irrigation schedules, we select the total rainfall from the day with the greatest amount of rainfall within five days before the second nitrogen application. This represents the amount of rain the optimized nitrogen management was able to tolerate. The same process calculated the moderate and light rain thresholds, but within three and one day(s) before the second nitrogen application, respectively.

With knowledge attributes calculated, we next search for ways to innovate the common practices of Cass County farmers (Fig. 3 and Fig. 4). Looking for innovations in the common practices of producers

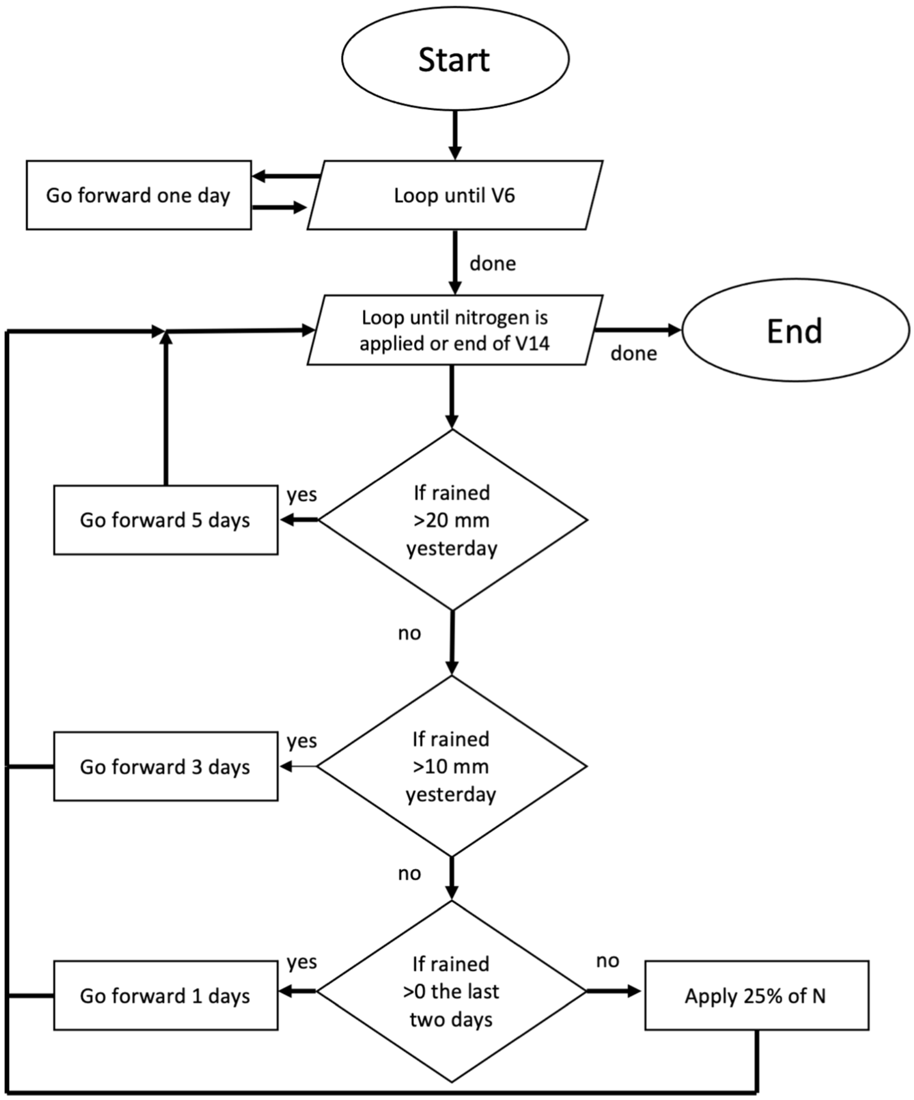

Fig. 4. Flow chart of common nitrogen practices in Cass County, Michigan.

Table 2
Knowledge attributes.

Knowledge attribute code	Description
w_{V6}	Total water during V6
w_{V7}	Total water during V7
w_{V8}	Total water during V8
w_{V9}	Total water during V9
w_{V10}	Total water during V10
w_{V11}	Total water during V11
w_{V12}	Total water during V12
w_{V13}	Total water during V13
w_{V14}	Total water during V14
w_{R1}	Total water during R1
m_h	Threshold for heavy rainfall
m_m	Threshold for moderate rainfall
m_l	Threshold for light rainfall

makes recommendations easy and understandable for existing practitioners to follow. One area for improvement in the existing system is how much irrigation is applied during each application. As described in Fig. 3, farmers in Cass County currently irrigate 10 mm of water during the vegetative phases of maize, and 20 mm during the reproductive stages of maize. These fixed application amounts are excellent targets for innovization since they only consider whether the plant is in the vegetative or reproductive stages. Optimizing irrigation application amount for individual growth stages (i.e., V6 through V14, and R1) would give the farmer better control to manage the water use of their crop. Additionally, an optimized set of application amounts per growth phase would be simple to communicate with farmers. To discover targeted application amounts for each physiological phase, we compared the optimized median values of w_{V6} through w_{R1} from the 30 years of optimized practices to the values of w_{V6} through w_{R1} brought about by 30 years of common practices in Cass County. These 30 years of common practices were realized by first designing an algorithm that simulates the decision-making of a farmer following common practices as described in Fig. 3. Let this simulated farmer be known as g^{com}. Then, the simulated farmer runs for all 30 years of weather data, and the of w_{V6} through w_{R1} are calculated from their management decisions. With the computer-optimized and the common-practice-based medians for w_{V6} through w_{R1}, the percentage difference is calculated between the two as follows:

$$\Delta\widetilde{w}_p = \left(\widetilde{w}_p^{opt} - \widetilde{w}_p^{com}\right) \Big/ \widetilde{w}_p^{com} \tag{3}$$

where, $p \in \{V6, \cdots, V14, R1\}$, $\widetilde{w}_p$ is the median water usage during physiological phase p for either common practices ($\widetilde{w}_p^{com}$) or optimized practices ($\widetilde{w}_p^{opt}$), and $\Delta\widetilde{w}_p$ is the median difference between common practices and optimized practices ($0 \leq \Delta\widetilde{w}_p \leq 1$). With the set of recommended percentage differences $\Delta W = \{\Delta\widetilde{w}_{V6}, \cdots, \Delta\widetilde{w}_{V14}, \Delta\widetilde{w}_{R1}\}$, we can then advise the farmer to alter the default irrigation application amount in common practices (i.e., either 10 mm in vegetative stages or 20 mm in reproductive stages) according to ΔW. Formally speaking, we would recommend:

$$i_p^{rec} = i_p + i_p * \Delta\widetilde{w}_p \tag{4}$$

where, i_p is the amount of irrigation applied during the physiological phase p according to common practices (i.e., $i_p \in \{10, 20\}$), and i_p^{rec} is the new recommended irrigation amount for this physiological growth phase. The timing of irrigation would remain intact from common practices. In summary, our recommended irrigation practice would take the form $I^{rec} = \{i_{V6}^{rec}, \cdots, i_{V14}^{rec}, i_{R1}^{rec}\}$, where each element in the vector I^{rec} is the amount of irrigation that is applied during the given physiological phase.

A similar innovization procedure occurs for improving the second nitrogen application. According to the common practices, before irrigating, farmers will wait for five consecutive days after a heavy precipitation event (i.e., greater than 20 mm), three days for a moderate precipitation event (i.e., greater than 10 mm), and two days after any light precipitation events. We hypothesized that these thresholds, denoted as m_h, m_m, and m_l, can be innovated. To test this hypothesis, we examined the precipitation of the days leading up to the optimal fertilizer applications. For each optimal result, we search for what has constituted a heavy, moderate, and light precipitation event in that optimal result, or m_h^{opt}, m_m^{opt}, and m_l^{opt}. In other words, we record the most extreme weather events (i.e., the amount of precipitation on the day with the most rain) five days before the second application, three days before the second application, and two days before the second application. We then take the medians of these three sets to obtain $\widetilde{m}_h^{opt}$, $\widetilde{m}_m^{opt}$, and $\widetilde{m}_l^{opt}$. Then, the percentage difference between m_h, m_m, and m_l in common practices (m_h^{com}, m_m^{com}, and m_l^{com}) and in the optimized results ($\widetilde{m}_h^{opt}$, $\widetilde{m}_m^{opt}$, and $\widetilde{m}_l^{opt}$) will define the deviation between all thresholds as follows:

$$\Delta\widetilde{m}_h = (\widetilde{m}_h{}^{opt} - m_h^{com}) / m_h^{com} \tag{5}$$

$$\Delta\widetilde{m}_m = (\widetilde{m}_m{}^{opt} - m_m^{com}) / m_m^{com} \tag{6}$$

$$\Delta\widetilde{m}_l = (\widetilde{m}_l{}^{opt} - m_l^{com}) / m_l^{com} \tag{7}$$

where, $\Delta\widetilde{m}_h$, $\Delta\widetilde{m}_m$, $\Delta\widetilde{m}_l$ are the percentage difference between the optimized rain thresholds and the common practices. From $\Delta\widetilde{m}_h$, $\Delta\widetilde{m}_m$, $\Delta\widetilde{m}_l$, recommendations can be made for an innovative threshold for what constitutes heavy, moderate, and light rain as follows. Together, these three recommendations will be known as the set $M^{rec} = \{m_h^{rec}, m_m^{rec}, m_l^{rec}\}$.

$$m_h^{rec} = m_h^{com} * \Delta\widetilde{m}_h \tag{8}$$

$$m_m^{rec} = m_m^{com} * \Delta\widetilde{m}_m \tag{9}$$

$$m_l^{rec} = m_l^{com} * \Delta\widetilde{m}_l \tag{10}$$

2.7. Validation

To validate the innovativeness of I^{rec} and M^{rec}, we measure the performance of four strategies. The first strategy represents farmers following common practices, denoted as the *common practice strategy*. The other three strategies are innovization based: 1) farmers only following irrigation recommendations I^{rec} (*irrigation recommendation strategy)*, 2) farmers only following nitrogen application recommendations of M^{rec} (*nitrogen recommendation strategy)*, and 3) farmers following both irrigation and nitrogen application recommendations (I^{rec} and M^{rec}) (*all recommendation strategy*). These strategies will measure the performance of I^{rec} and M^{rec} individually, as well as the recommendations enacted simultaneously. Performance is measured in yield, water efficiency, and nitrogen leaching, which DSSAT simulates, given the weather for the season. These strategies will also demonstrate the sensitivity of the irrigation and nitrogen parameters on our agricultural objectives. We measured these performance metrics under as many validation seasons of weather as possible to ensure statistical rigor. Since there are plentiful weather records in Southwest Michigan, we gathered 420 validation seasons of weather available. This included 30 years of historical weather data (1989–2018), and 14 weather stations in Southwest Michigan (Figure S1) ($30 \times 14 = 420$). These climatologically similar sites are in Allegan, Bainbridge, Benton Harbor, Berrien Springs, Dowagiac, Fennville, Grand Junction, Hart, Keeler, Lawrence, Lawton, Oshtemo, Scottdale, and South Haven counties. All weather data was retrieved from MSU Enviroweather and the GHCN. Of these 420 validation seasons, 159 are climatologically dry, 135 are climatologically normal, and 126 are climatologically wet.

With these 420 validations seasons, three statistical tests measure the efficacy of the amended practices: g_I^{rec} versus g_I^{com}, g_M^{rec} versus g_M^{com}, and g_{MI}^{rec} versus g_{MI}^{com}. Under each test, 420 DSSAT simulations of the *common practice strategy* are compared to 420 DSSAT simulations of amended practices according to yield, water efficiency, and leaching. Since the data did not consistently follow a normal distribution, the Wilcoxon Rank Sum test was used (Hollander et al., 2013) to test whether these three-performance metrics were different between the two runs.

3. Results and discussions

3.1. Performance of irrigation recommendation strategy

Overall, the *irrigation recommendation strategy* (Table 3) increased yields over the *common practice strategy*, with a mean increase of 271.11 kg/ha per year (Table 4). This increase was statistically significant, with a *p-value* of 3.5% (i.e., < 5%) (Table S2). Of the validation seasons, 78.83% of seasons saw gains in yield, and the gains far outweighed the losses. The average gain in yield was 364.64 kg/ha per year compared to the *common practice strategy*, as opposed to an average loss in yield of 93.03 kg/ha (Fig. 5). Thus, on a yearly basis, the benefits of the *irrigation recommendation strategy* far outweighed the costs. This is further illustrated when considering how much a farmer is expected to gain over the course of 30 years. To do so, we calculated the average cumulative net increase in yields across all study sites over thirty years (Fig. 6). To

Table 3
Knowledge attributes recommendations.

Irrigation Recommendations	
Knowledge attribute code	**Recommended change from common practices (mm)**
w_{V6}	−9%
w_{V7}	+31%
w_{V8}	+13%
w_{V9}	+50%
w_{V10}	+60%
w_{V11}	−0.5%
w_{V12}	−0.5%
w_{V13}	+14%
w_{V14}	+13%
w_{R1}	−10%
Nitrogen recommendations	
Knowledge attribute code	**Recommended change from common practices (mm)**
m_h	−60%
m_m	−64%
m_l	+∞%*

*A change from 0 to 0.8.

Table 4
The overall performance of the various strategies as well as its performance over different climate scenarios. Superscripts +, −, and ≈ denote a statistical improvement, statistical worsening, or no statistical change from the *common practice strategy,* respectively.

Strategy	Mean yield (kg/ha)	Mean leaching (kg/ha)	Mean water efficiency (kg/mm·ha)
	Performance across all years		
Common practice	*7054.03*	*23.24*	*297.88*
Irrigation recommendation	7325.14^{+}	$22.37^{\approx}$	231.43^{-}
Nitrogen recommendation	$7072.43^{\approx}$	$23.28^{\approx}$	$299.81^{\approx}$
All recommendations	7333.21^{+}	$22.34^{\approx}$	231.67^{-}
	Performance during dry years		
Common practice	*5934.72*	*14.08*	*222.86*
Irrigation recommendation	$6080.56^{\approx}$	$13.33^{\approx}$	$175.81^{\approx}$
Nitrogen recommendation	$5937.12^{\approx}$	$13.75^{\approx}$	$224.16^{\approx}$
All recommendations	$6104.40^{\approx}$	$13.23^{\approx}$	$176.43^{\approx}$
	Performance during normal years		
Common practice	7716.19	28.22	368.66
Irrigation recommendation	$7902.55^{\approx}$	$28.53^{\approx}$	290.51^{-}
Nitrogen recommendation	$7735.88^{\approx}$	$28.41^{\approx}$	$371.34^{\approx}$
All recommendations	$7907.21^{\approx}$	$28.53^{\approx}$	290.66^{-}
	Performance during wet years		
Common practice	*7757.02*	*29.46*	*316.72*
Irrigation recommendation	8256.10^{+}	$27.04^{\approx}$	237.56^{-}
Nitrogen recommendation	$7775.88^{\approx}$	$29.67^{\approx}$	$317.56^{\approx}$
All recommendations	8248.21^{+}	$27.07^{\approx}$	237.41^{-}

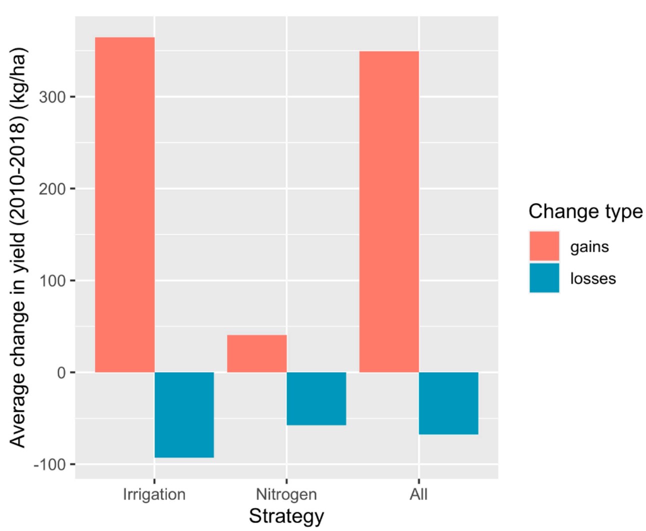

Fig. 5. The average gains and losses in yield between 1989 and 2018.

summarize, a farmer can expect an average increase in yield between 6964.18 kg/ha and 7904.82 kg/ha by the end of 30 years (Fig. 6) over the *common practice strategy*. Encouragingly, no farmer experienced an increase below 6288 kg/ha over the *common practice strategies* during the thirty-year period, and one scenario even experienced a 9720 kg/ha increase in yield. These increases imply that yield is highly sensitive to the irrigation parameters in the innovization framework. In summary, despite a minority of validation seasons with minor decreases in yield, the *irrigation recommendation strategy* consistently results in significantly increased yields compared to the *common practice strategy*. Furthermore, Nandan (2021) supports these assertions by demonstrating the potential impacts of designed irrigation scheduling on corn yields in the Midwest USA under interannual precipitation variability.

These dramatic improvements in yield came at the expense of water use efficiency. Overall, there was a mean decrease in water use efficiency of 66.45 kg/mm·ha across all scenarios compared to the *common practice strategy*. This decrease was statistically significant, with a *p-value* of 0.3% (i.e., < 5%) (Table S2). Furthermore, 80.67% of scenarios had worse water use efficiency than the *common practice strategy*, and these worse scenarios were of a greater magnitude (on average 86.25 kg/mm·ha worse) than the improved scenarios (on average 4.57 kg/mm·ha improved) (Table 4). These outcomes suggest that water use efficiency is sensitive to the irrigation parameters in the innovization model. Though not the desired result, such a decrease in water use efficiency in the Midwest is an arguably worthwhile tradeoff for the increased yields brought about by the *irrigation recommendation strategy* (Andresen et al., 2011).

The *irrigation recommendation strategy* improved leaching slightly over the *common practice strategy*, with the mean leaching improving by 0.9 kg/ha per year (Table 4). However, this improvement is not statistically significant since the decrease in leaching had a *p-value* of 64% (i.e., greater than 5%) (Table S2), suggesting that leaching is only minimally sensitive to the set irrigation parameters in our innovization framework. And even if leaching is not significantly changed, as the *p-value* suggests, this is still a promising outcome since it suggests that the *irrigation recommendation strategy* can increase yields with no impacts on nitrogen leaching. Also, two years (2001 and 2008) had sizeable decreases in leaching, which resulted in an average cumulative net decrease of 26.96 kg/ha in leaching over 30 years (Fig. 7). This was most likely caused by the difference in irrigation applications around the second nitrogen application. In the years with significantly decreased leaching, the *irrigation recommendation strategy* consistently applied less irrigation when the irrigation application date was near the second nitrogen application date. This also would explain why yields jumped up on these years as increased nitrogen uptake would help improve yields during this critical physiological phase. However, beyond 2001 and 2008, the cumulative net decrease was relatively unstable, with a maximum reduction in yield of 61.57 kg/ha and a minimum reduction of 8.87 kg/ha. In summary, despite minor improvements, leaching did not significantly change under the *irrigation recommendation strategy*, which is a good outcome considering the significant improvements in yield. This contrasts with the literature, which clearly states that the amount and timing of irrigation greatly influences the nitrate leaching. Altering the irrigation schedule to avoid coincidental N application helps crops in uptaking N during critical crop growth stages and hence lessen leaching (Singh, 2021). Gheysari (2009) have highlighted the impact of different levels of irrigation on nitrate leaching in corn and emphasized that if irrigation and nitrogen application timing can be managed efficiently on the field, the impact on nitrate leaching will be less without comprising corn yields. Therefore, the *irrigation recommendation strategy* failed to achieve potential statistically significant improvements in leaching. The climate of the validation season affected the performance of the *irrigation recommendation strategy*. With regards to yield, there is no statistically significant change from the *common practice strategy* during dry and normal years, while there is a statistically significant increase in yield during wet years (Table 4, S2). This suggests that there may have been a deficiency in the *common practice strategy* during wet years that the *irrigation recommendation strategy* addressed. It also emphasizes the relative sensitivity of yield to the irrigation parameters of the innovization model during wet years compared to dry and normal years. Concerning leaching, climate variabilities brought about little change in the performance of the *irrigation recommendation strategy*: dry, wet, and normal years all had no significant change in leaching from the *common practice strategies* (Table 4, S2). Finally, though there was a drop in mean water use efficiency during dry years, the change was not statistically significant (i.e., a *p-value* of 15%) (Table S2). However, water use efficiency significantly decreased from the *common practice strategy* for normal and wet years. Overall, the

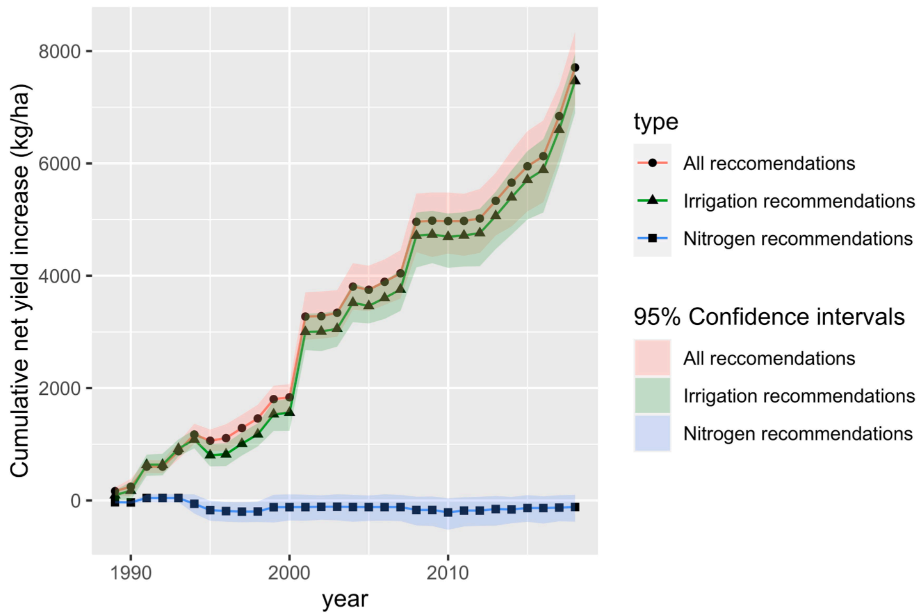

Fig. 6. Cumulative net increase in yield between *irrigation recommendation strategy, nitrogen recommendation strategy, and all recommendation strategy* strategies from common practice strategy. The lines' transparent margins represent the 95% confidence intervals of that average value.

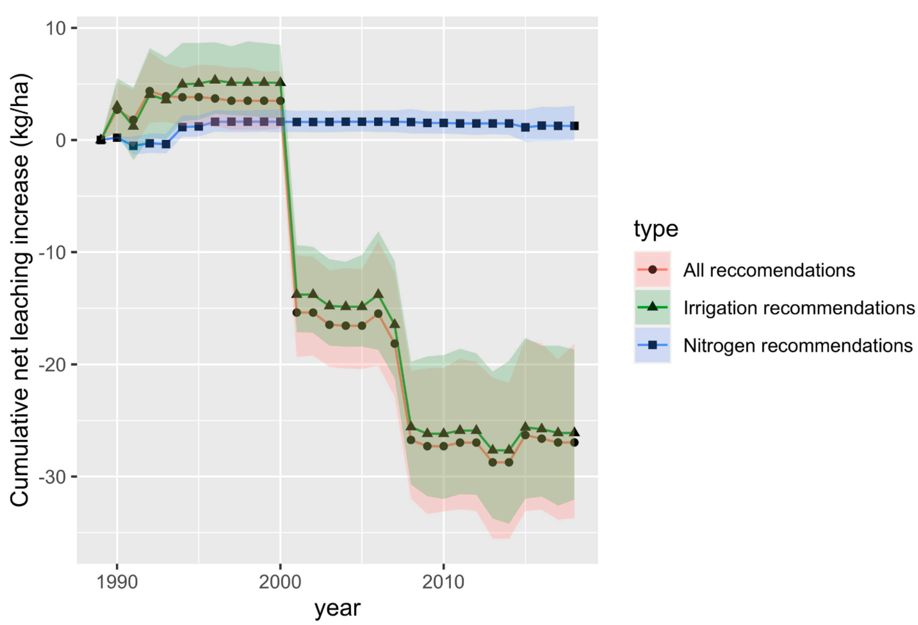

Fig. 7. The cumulative net change in leaching between *irrigation recommendation strategy*, *nitrogen recommendation strategy*, and *all recommendation strategy* from common practice strategy. The lines' transparent margins represent the 95% confidence intervals of that average value.

innovizations had the least amount of impact during dry years and the most amount of impact during wet years.

3.2. Performance of nitrogen recommendation strategy

Compared to the *irrigation recommendation strategy,* the *nitrogen recommendation strategy* (Table 3) offered no clear benefits or drawbacks. With respect to yield, though there are minor drops in yield between the mean yield of the *nitrogen recommendation strategy* and the *common practice strategy* (Table 4)*,* the two strategies are statistically nearly identical (*p-value* of 90%) (Table S2). The gains of the strategy were smaller in comparison to the losses (40.7 kg/ha in gains versus 57.5 kg/ha in losses) (Fig. 5), and only 30% of the scenarios were gains. The above findings demonstrate that yield is insensitive to nitrogen application timing in our innovization framework. Finally, the cumulative 30-year yield across the 14 study sites hovered around 0 kg/ha change from the *common practice strategies* (Fig. 6). In summary, despite consistent losses, there was no statistical change in yield between the *nitrogen recommendation strategy*.

The *nitrogen recommendation strategy* also had very little change in water use efficiency or leaching from the *common practice strategy*. Nominally, there is a minor mean increase in water use efficiency (1.92 kg/mm·ha) (Table 4), but not enough to be statistically significant (*p-value* of 91%) (Table S2). Leaching similarly had a mean increase between the *common practice* and the *nitrogen recommendation strategies* (23.28 versus 23.24 kg/ha) (Table 4)*,* but not to a statistically significant extent (*p-value* of 96%) (Table S2). Therefore, there is no significant change in environmental impact between the two strategies and leaching and water efficiency were largely insensitive to nitrogen application timing in our framework. Considering this lack of improvements, the *irrigation recommendation strategy* is a clear better option than the *nitrogen recommendation strategy*. Finally, climate has no statistical impact on the performance of the *nitrogen recommendation strategy*. Though minor differences exist in performance across dry, normal, and wet years, none of them are statistically significant. Across the board, the *nitrogen recommendation strategy* has no statistical effect on yield, water use efficiency, or nitrogen leaching.

3.3. Performance of all recommendation strategy

The *all recommendation strategy* differs from the *common practice strategy* similarly to the *irrigation only strategy*. There is a statistically significant (*p-value* of 3.2%) (Table S2) mean increase in yield of 279.18 kg/ha per year over the *common practice strategy* (Table 4), and 77% of scenarios resulted in an increase of yields. Of this 77%, the average increase was 349.4 kg/ha, which is slightly lower than the increases from the *irrigation recommendation strategy* at 364.6 kg/ha (Fig. 5). On the other hand, the 23% of scenarios resulting in yield losses from the *common practice strategy* were on average lower than the *irrigation recommendation strategy* at 67.57 kg/ha (Fig. 5). Cumulatively over the 30-year study period, the *all recommendation strategy* modestly outpaces the *irrigation only strategy* by 348.9 kg/ha (Fig. 6). However, despite these differences between the *all recommendation strategy* and the *irrigation only strategy,* there no significant difference between the yields of both strategies (*p-value* of 94%). Overall, the performance of the *all recommendation strategy* is statistically identical to the *irrigation recommendation strategy* with respect to yield.

Similar to the *irrigation recommendation strategy*, the *all recommendation* strategy suffered from setbacks in water use efficiency compared to the *common practice strategy*. Specifically, there was a mean decrease in water use efficiency by 66.21 kg/mm·ha (Table 4), which was statistically significant (*p-value* of 0.3%) (Table S2). Compared to the setbacks in the *irrigation recommendation strategy,* the mean water use efficiency in the *all recommendation strategy* was nominally worse (by 0.30 g/mm·ha) (Table 4). However, the two strategies both had identical rates of water use efficiency decrease from the *common practice strategy* (*p-value* of 96%). As described before, this is an arguably worthwhile tradeoff for the increase in yield in the Midwest. With respect to leaching, the lack of improvements or setbacks in the *all recommendation strategy* are identical to the *irrigation recommendation strategy* by all statistical measures (i.e., same means, *p-value* of 97%) (Table S2). The effects of climate on performance are similarly identical to the effects of climate on the *irrigation recommendation strategy*.

Compared to the current best-performing strategy, *irrigation recommendation strategy,* the changes in yield, leaching, and water use efficiency are statistically identical, despite nominal differences between the two. However, if one considers the complexity of the proposed practice and, subsequently, its appeal to farmers, the *irrigation recommendation strategy* is the better choice. Therefore, though they are statistically identical, the *irrigation recommendation strategy* is arguably the practice worth adopting. Meanwhile, the *nitrogen recommendation strategy* offers no statistical improvement to the *common practice strategy* and thus should not be recommended to farmers.

3.4. Study implications

The gains in the *irrigation recommendation* and *all recommendation* strategies are also financially worthwhile improvements over the *common practice strategy*. For the *irrigation recommendation strategy,* a farmer in Cass County would gain on average 6,900 kg/ha in yield over 30 years (with negligible changes in leaching) just by slightly altering their irrigation amounts according to the vegetative stage. To grasp the impact of a 6,900 kg/ha improvement in yield, consider the following example. The average price of corn in the US was ¢12 per kg between 1989 and 2018 (FarmDoc, 2021), and thus a farmer with a 500-hectare farm would gain $427,612.86 over a thirty-year period. This is a sizable amount increase with a very minimal shift from common practices in the region.

Though the efficacy of this study is bounded by the study area, it can be easily expanded on a regional scale. To do so, Extension Educators would collect the common practices of different regions for different cultivars and soil types. Then, the Extension Educators would search for ways to optimize the common practices for each specific combination of region, cultivar, and soil types. Next, an innovization software platform would analyze how those variables could be improved for the study region. All of these individual rules could then be aggregated into a single decision support tool for a region, where farmers could easily access simple amendments to their common regional practices. Alternatively, in areas with low internet connectivity, Extension Educators could distribute the recommendations through simple pamphlets. Such an optimization platform excellently melds human decision-making and computer optimization, and outputs results that farmers can actually apply to their fields.

4. Conclusions

This study examined the efficacy of agricultural innovization under three different strategies: the *irrigation recommendation strategy,* the *nitrogen recommendation strategy,* and the *all recommendation strategy*. Two of the three strategies (i.e., the *irrigation recommendation strategy* and *all recommendation* strategy) both statistically significantly improved yields with no impact on nitrogen leaching. However, both strategies resulted in loss in water use efficiency. Though the drop was not critically significant for the Midwest, it is an area of improvement in future studies. Future studies should add a water efficiency objective to ensure that the innovization outputs solutions that are near-optimal in water efficiency as well as in yield, total water use, and leaching. Overall, the *irrigation recommendation strategy* is the best option to recommend to farmers, due to its high yield, lack of nitrogen leaching, and relative simplicity.

Another room for growth is finding innovations that are specific to climate variabilities. In this study, the *irrigation recommendation strategy* only improved irrigation during wet seasons (Table 4), with normal and dry seasons exhibiting no statistically significant change from the *common practice strategy*. Though this is a promising outcome, there is room for improvement. Future studies should seek to perform innovizations on specific climate scenarios, which can then be designed into more intelligent amendments to the *common practice strategy*. This is well within reason, since seasonal climate forecasts are skillful enough to predict whether a growing season will be wet, normal, or dry climatologically.

Other areas of future work include ground truth studies and different agricultural conventions. Specifically, though the model was thoroughly calibrated and validated on the study site, future work should attempt to implement the recommended practices in the field in order to validate their efficacy in the real world. Finally, the framework can and should be applied to other agricultural conventions, such as organic or regenerative farming. This is well within the capacity of our proposed framework and would entail changing the decision variables and objectives to those unique to the given agricultural system.

In summary, this study demonstrates the efficacy of agricultural innovization. By considering the common practices of real farmers in a study region and optimizing the practices for 30 years of weather data, we generate practical and effective recommendations for farmers. By following our recommendations, simulated farmers were able to gain a 6,900 kg/ha increase in yield over thirty years of management. Moreover, these gains only incurred negligible changes in leaching levels and increased water use. Such methods are promising within a food system that needs to sustainably increase yields to feed an increasingly large and affluent global population.

CRediT authorship contribution statement

Ian Kropp: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft, Writing – review & editing. **A. Pouyan Nejadhashemi:** Supervision, Conceptualization, Project administration, Methodology, Funding acquisition, Writing – review & editing. **Prakash Jha:** Writing – original draft, Resources, Data curation, Writing – review & editing. **J. Sebastian Hernandez-Suarez:** Methodology, Software, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data statement

The source code for this project is available on the following public Git repository: https://gitlab.msu.edu/dsi-lab/agovization.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2022.107143.

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