

1 Highlights

2 **Fixed versus adaptive irrigation and fertilizer management under** 3 **weather uncertainty: a comparative study using genetic algorithm** 4 **optimization and model predictive control**

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- 6 • Comparative framework: fixed GA strategy vs. adaptive MPC ap-
7 proach
- 8 • Bayesian Optimization (TPE) for automated MPC weight tuning
- 9 • Risk-return tradeoff analysis via coefficient of variation
- 10 • Stochastic weather scenarios: drought, normal, wet conditions
- 11 • Decision guidance: MPC for risk-averse, GA for drought-prone regions

12 Fixed versus adaptive irrigation and fertilizer
13 management under weather uncertainty: a comparative
14 study using genetic algorithm optimization and model
15 predictive control

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17 **Abstract**

Climate variability poses significant challenges to agricultural resource management, as fixed irrigation and fertilization strategies optimized for expected conditions may perform poorly when actual weather deviates from assumptions. This paper presents a comparative study of fixed versus adaptive resource management strategies under weather uncertainty. We develop an adaptive approach combining Model Predictive Control (MPC) with Bayesian Optimization (BO) for irrigation and fertilizer scheduling, building on a crop growth model that captures delayed nutrient absorption via finite impulse response (FIR) convolution and cumulative stress tracking via exponential moving average (EMA) filtering. The MPC controller solves a constrained finite-time optimal control (CFTOC) problem at each decision epoch, balancing crop value maximization against input costs and nutrient stress penalties, with BO using Tree-structured Parzen Estimators (TPE) to tune controller parameters for robust performance. Evaluated on corn production in Iowa across 21 stochastic weather scenarios ranging from normal to extreme conditions, we compare three strategies: farmer baseline practices, a genetic algorithm (GA) that optimizes a fixed strategy for drought conditions, and adaptive MPC that re-optimizes daily. Results reveal a fundamental tradeoff between mean revenue and consistency. The fixed GA achieves the highest mean revenue (\$796/acre) but with substantial variance, while MPC achieves lower mean revenue (\$750/acre) but with the lowest co-

efficient of variation (15.4% vs 16.6%). MPC outperforms GA in 12 of 21 scenarios—particularly in normal and wet conditions—while GA excels in the drought conditions for which it was optimized. These findings provide practical guidance: when weather patterns are predictable and match optimization assumptions, fixed strategies maximize returns; when weather is uncertain, adaptive MPC provides valuable risk reduction through consistent performance across diverse conditions.

18 *Keywords:* precision agriculture, model predictive control, Bayesian
 19 optimization, weather uncertainty, adaptive control,

20 1. Introduction

21 Climate change is increasing the frequency and severity of extreme weather
 22 events, posing significant challenges to agricultural production [1]. Traditional
 23 approaches to irrigation and fertilizer scheduling rely on fixed strategies—
 24 either following agronomic best practices or optimized once for expected
 25 conditions—that cannot adapt when actual weather deviates from assumptions.
 26 As drought, heat waves, and other extremes become more common, there is
 27 growing need for adaptive resource management strategies that can respond
 28 to observed conditions in real time. Recent work on digital-twin frameworks
 29 for precision agriculture [2, 3] and computational approaches to agricultural
 30 resource delivery [4, 5] has demonstrated the potential for model-based
 31 optimization in farming systems.

32 In a companion paper currently under review [6], we developed a generalized
 33 crop growth model based on coupled ordinary differential equations (ODEs)
 34 that captures the nonlinear dynamics of plant development under varying
 35 environmental conditions. The model tracks five state variables—plant
 36 height, leaf area, number of leaves, flower size, and fruit biomass—each
 37 governed by logistic growth with time-varying parameters modulated by
 38 nutrient factors. These factors quantify how well actual water, fertilizer,
 39 temperature, and solar radiation levels match the plant’s physiological
 40 expectations, with delayed absorption modeled via finite impulse response (FIR)
 41 convolution and cumulative stress tracked via exponential moving average
 42 (EMA) filtering. Using a genetic algorithm (GA), we showed that optimized
 43 irrigation and fertilizer strategies can achieve 16% higher net revenue than
 44 conventional farmer practices under drought conditions.

However, the GA approach optimizes a *fixed* strategy—specifying application frequencies and amounts that remain constant throughout the growing season. While effective when actual conditions match the optimization assumptions, such open-loop strategies cannot adapt to unexpected weather events. If a drought is more severe than anticipated, or an unexpected heat wave occurs, the pre-computed strategy may be far from optimal.

This paper extends our previous work by developing an *adaptive* approach using Model Predictive Control (MPC). MPC is a closed-loop control strategy that repeatedly solves an optimization problem over a finite horizon, applies only the first control action, then re-optimizes based on updated state and disturbance information [7]. This receding-horizon structure enables the controller to adapt to changing conditions while maintaining optimality over the planning horizon.

Applying MPC to agricultural systems presents several challenges. First, the nonlinear crop dynamics with delayed absorption effects complicate the optimization problem. Second, the controller must balance multiple competing objectives: maximizing crop value, minimizing input costs, and avoiding nutrient stress that degrades plant health. Third, the relative importance of these objectives depends on weather conditions and growth stage, requiring careful tuning of the cost function weights. To address this last challenge, we employ Bayesian Optimization (BO) [8] to automatically tune the MPC parameters for robust performance across diverse weather scenarios.

Our contributions are:

1. Formulation of a constrained finite-time optimal control (CFTOC) problem for daily irrigation and fertilizer scheduling that accounts for delayed nutrient absorption and cumulative stress effects.
2. A receding-horizon MPC implementation that adapts resource allocation based on observed weather conditions, with parameters tuned via Bayesian optimization using Tree-structured Parzen Estimators (TPE) [9].
3. Systematic comparison of three resource management strategies—farmer baseline, fixed GA-optimized, and adaptive MPC—across 21 stochastic weather scenarios spanning normal to extreme conditions.
4. Characterization of the risk-return tradeoff between fixed and adaptive strategies, identifying the conditions under which each approach excels.

Our results reveal that the choice between fixed and adaptive strategies involves a fundamental tradeoff. The GA-optimized fixed strategy achieves

82 higher mean revenue but with greater variance, while MPC sacrifices some
 83 peak performance for consistency across diverse weather conditions. These
 84 findings provide practical guidance for agricultural decision-making under
 85 climate uncertainty.

86 2. Crop growth model

87 We employ the crop growth model developed in [6], which we briefly
 88 summarize here. The model treats the plant as a dynamic system with state
 89 vector $x = [x_h, x_A, x_N, x_c, x_P]^T$ representing plant height (m), leaf area per
 90 leaf (m^2), number of leaves, flower size (spikelets), and fruit biomass (kg).
 91 Control inputs are irrigation u_w (inches/hour) and fertilizer u_f (lbs/hour),
 92 while disturbances include precipitation d_S (inches/hour), temperature d_T
 93 ($^{\circ}\text{C}$), and solar radiation d_R (W/m^2).

94 2.1. Logistic growth dynamics

95 Each state variable follows logistic growth with time-varying parameters:

$$\frac{dx}{dt} = \hat{a}_x(t) \cdot x(t) \left(1 - \frac{x(t)}{\hat{k}_x(t)} \right) \quad (1)$$

96 where $\hat{a}_x(t)$ is the effective growth rate and $\hat{k}_x(t)$ is the effective carrying
 97 capacity, both modulated by nutrient factors. This equation admits a closed-
 98 form solution:

$$x(t + \Delta t) = \frac{\hat{k}_x(t)}{1 + \left(\frac{\hat{k}_x(t)}{x(t)} - 1 \right) \exp(-\hat{a}_x(t)\Delta t)} \quad (2)$$

99 enabling exact time-stepping without numerical integration error.

100 2.2. Delayed absorption via FIR convolution

101 Plants do not immediately utilize applied nutrients; there is a physiologically-
 102 mediated delay between application and absorption. We model this using
 103 finite impulse response (FIR) convolution with Gaussian kernels:

$$g[k] = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left\{ -\frac{(k - \mu)^2}{2\sigma^2} \right\} \quad (3)$$

104 where σ is the temporal spread characterizing absorption duration. We set
 105 $\mu \approx 1.96\sigma$ so that 95% of the kernel mass lies within $[0, 2\mu]$. Different
 106 nutrients have different metabolic timescales: $\sigma_w = 30$ hours for water (rapid
 107 uptake), $\sigma_f = 300$ hours for fertilizer (slow root absorption), and $\sigma_T = \sigma_R =$
 108 30 hours for temperature and radiation.

109 The delayed (absorbed) signal is computed as:

$$\bar{u}[k] = \sum_{n=0}^{L-1} g[n] \cdot u[k-n] \quad (4)$$

110 where L is the FIR horizon chosen to capture 95% of the kernel mass.

111 2.3. Cumulative stress tracking

112 While FIR convolution captures delayed absorption, plants also accu-
 113 mulate stress from sustained deviations from optimal conditions. We track
 114 cumulative divergence using exponential moving average (EMA) filtering:

$$\Delta_u[k] = \beta_\Delta \cdot \Delta_u[k-1] + (1 - \beta_\Delta) \cdot \delta_u[k] \quad (5)$$

115 where $\delta_u[k]$ is the instantaneous anomaly (relative deviation from expected
 116 cumulative absorption) and $\beta_\Delta = 0.95$ provides long memory of past stress
 117 events.

118 2.4. Nutrient factors

119 The cumulative divergence is converted to a nutrient factor $\nu \in [0, 1]$ via
 120 exponential decay with additional EMA smoothing:

$$\nu_u[k] = \beta_\nu \cdot \nu_u[k-1] + (1 - \beta_\nu) \cdot \exp\{-\alpha \Delta_u[k]\} \quad (6)$$

121 where $\alpha = 3$ ensures $\nu \approx 0.05$ when $\Delta = 1$ (complete divergence). The
 122 nutrient factor equals 1 when inputs match expectations and decays toward
 123 0 under sustained stress.

124 The effective growth parameters are computed as geometric means of rel-
 125 evant nutrient factors. For example, fruit biomass carrying capacity depends
 126 on all inputs and prior vegetative growth:

$$\hat{k}_P(t) = k_P \left(\nu_w \nu_f \nu_T \nu_R \frac{\hat{k}_h}{k_h} \frac{\hat{k}_A}{k_A} \frac{\hat{k}_c}{k_c} \right)^{1/7} \quad (7)$$

127 Full details of the parameter relationships are provided in [6].

128 3. Stochastic weather scenario generation

129 To evaluate controller robustness, we generate a suite of stochastic weather
 130 scenarios from historical baseline data. Each scenario applies perturbations
 131 representing different climate conditions, from normal variability to extreme
 132 events.

133 3.1. Generation process

Let the historical hourly time series be

$$d_S^{\text{hist}}[k] \geq 0 \quad (8)$$

$$-20 \leq d_T^{\text{hist}}[k] \leq 50 \quad (9)$$

$$d_R^{\text{hist}}[k] \geq 0 \quad (10)$$

134 for $k = 0, \dots, K - 1$ where K is the length of the growing season in hours,
 135 respectively representing precipitation (inches), temperature ($^{\circ}\text{C}$), and solar
 136 radiation (W/m^2). Then, let a stochastic weather scenario be defined by the
 137 parameters

$$\theta = (s_S, s_T, s_R, \eta, \mathcal{D}, \mathcal{H}, \mathcal{C}) \quad (11)$$

138 where

- 139 • s_S is the precipitation scaling factor
- 140 • s_T is the temperature offset
- 141 • s_R is the radiation scaling factor
- 142 • η is the relative noise level (a fraction of the historical standard deviation)
- 143
- 144 • \mathcal{D} is a drought event
- 145 • \mathcal{H} is a heat wave event
- 146 • \mathcal{C} is a cold snap event

147 Each of the event types $(\mathcal{D}, \mathcal{H}, \mathcal{C})$ are defined by three parameters:

$$[k_0, \kappa, \iota] \quad (12)$$

148 where

- 149 • k_0 is the hour when the event begins
- 150 • κ is the duration of the event in number of hours
- 151 • $\iota \in [0, 1]$ is the intensity, with 1 being the most intense

152 3.1.1. Global scaling and offset

153 Initialize the synthetic environmental disturbance time series after apply-
 154 ing the global adjustments (s_S, s_T, s_R) for $k = 0, \dots, K - 1$ as below

$$\begin{aligned}
 d_S^{(1)}[k] &= s_S d_S^{\text{hist}}[k] && \text{(scaling)} \\
 d_T^{(1)}[k] &= d_T^{\text{hist}}[k] + s_T && \text{(offset)} \\
 d_R^{(1)}[k] &= s_R d_R^{\text{hist}}[k] && \text{(scaling)}
 \end{aligned} \tag{13}$$

155 3.1.2. Add white noise

If $\eta > 0$, draw independent white noise sequences

$$\varepsilon_T[k] \sim \mathcal{N}(0, (\eta\sigma_T)^2) \tag{14}$$

$$\varepsilon_R[k] \sim \mathcal{N}(0, (\eta\sigma_R)^2) \tag{15}$$

156 where σ_T and σ_R are the standard deviations of the historical temperature
 157 and radiation time series, respectively.

We then smooth the white noise with a moving average over $m_T = 24$ hours for temperature and $m_R = 12$ hours for radiation, as we will only apply the noise to the radiation during the day time (when it is not as close to zero).

$$\bar{\varepsilon}_T = \frac{1}{m_T} \sum_{n=0}^{m_T-1} \varepsilon_T[k - n] \tag{16}$$

$$\bar{\varepsilon}_R = \frac{1}{m_R} \sum_{n=0}^{m_R-1} \varepsilon_R[k - n] \tag{17}$$

We then add that noise to the signals:

$$d_T^{(2)}[k] = d_T^{(1)}[k] + \bar{\varepsilon}_T[k] \tag{18}$$

$$d_R^{(2)}[k] = d_R^{(1)}[k] + \mathcal{M}_{\text{day}} \bar{\varepsilon}_R[k] \tag{19}$$

158 where

$$\mathcal{M}_{\text{day}} = \{k | d_R^{\text{hist}}[k] > d_R^{\text{day}}\} \quad (20)$$

159 and we choose the threshold $d_R^{\text{day}} = 10 \text{ W/m}^2$. Precipitation is unchanged in
160 this step, so

$$d_S^{(2)}[k] = d_S^{(1)}[k] \quad (21)$$

161 If $\eta = 0$, then we let $(d_S^{(2)}, d_T^{(2)}, d_R^{(2)}) = (d_S^{(1)}, d_T^{(1)}, d_R^{(1)})$.

162 3.1.3. Drought injection

163 A drought event is

$$\mathcal{D} = [k_0, \kappa, \iota] \quad (22)$$

164 For each event, we define the affected hourly index set as

$$\mathcal{I} = \{k_0, k_0 + 1, \dots, \min(k_0 + \kappa - 1, K - 1)\} \quad (23)$$

165 and then apply the intensity scaling to those indices with

$$d_S^{(3)}[k] \leftarrow (1 - \iota)d_S^{(2)}[k] \quad \text{for all } k \in \mathcal{I} \quad (24)$$

166 Temperature and radiation are unchanged in this step, so

$$d_T^{(3)}[k] = d_T^{(2)}[k] \quad \text{and} \quad d_R^{(3)}[k] = d_R^{(2)}[k] \quad (25)$$

167 3.1.4. Heat wave injection

168 A heat wave event is

$$\mathcal{H} = [k_0, \kappa, \iota] \quad (26)$$

169 where k_0 and κ have the same meanings they did for the drought event, but
170 now ι is the peak temperature add (an offset rather than a scaling factor).

171 We then construct a ramp-up, hold, and ramp-down for the heat wave. Let

$$\kappa_{\text{ramp}} = \max(1, 0.1\kappa) \quad (27)$$

172 i.e. either one tenth of the heat wave duration or at least one hour. Then,
173 let

$$\kappa_{\text{hold}} = \kappa - 2\kappa_{\text{ramp}} \quad (28)$$

174 to account for the ramp-up and ramp-down.

175 We can then define

176 • ramp-up: $w_{\text{up}}[k] = \frac{k}{\kappa_{\text{ramp}} - 1}$ for $k = 0, \dots, \kappa_{\text{ramp}} - 1$

177 • ramp-up: $w_{\text{hold}}[k] = 1$

178 • ramp-down: $w_{\text{down}}[k] = \frac{k}{\kappa_{\text{ramp}} - 1}$ for $k = 0, \dots, \kappa_{\text{ramp}} - 1$

179 and concatenate to form the heat wave window

$$w_{\text{heat}} = [w_{\text{up}}, w_{\text{hold}}, w_{\text{down}}] \quad (29)$$

180 Applying the heat wave to the temperature time series, we obtain

$$d_T^{(4)}[k] \leftarrow d_T^{(3)}[k] + \iota w_{\text{heat}}[k - k_0] \quad (30)$$

181 for $k = k_0, k_0 + 1, \dots, \min(k_0 + \kappa - 1, K - 1)$. Precipitation and radiation are
182 unchanged in this step, so

$$d_S^{(4)}[k] = d_S^{(3)}[k] \quad \text{and} \quad d_R^{(4)}[k] = d_R^{(3)}[k] \quad (31)$$

183 *3.1.5. Cold snap injection*

184 A cold snap event is

$$\mathcal{C} = [k_0, \kappa, \iota] \quad (32)$$

185 where k_0 and κ have the same meanings they did for the heat wave event,
186 but ι is now the magnitude of the lowest temperature drop. A cold snap
187 window is constructed in the same manner as the heat wave window and the
188 temperature time series becomes

$$d_T^{(4)}[k] \leftarrow d_T^{(4)}[k] - \iota w_{\text{heat}}[k - k_0] \quad (33)$$

189 for $k = k_0, k_0 + 1, \dots, \min(k_0 + \kappa - 1, K - 1)$. Note: we have used $d_T^{(4)}[k]$ on the
190 righthand side because we want to reflect that a heat wave may have already
191 been applied.

192 *3.1.6. Clipping to physical bounds*

Finally, we check to ensure that the transformations above have not violated the bounds on the input disturbances specified in equations 10. If they have, we clip the values as below

$$d_S^{\text{syn}}[k] = \max(0, d_S^{(4)}[k]) \quad (34)$$

$$d_T^{\text{syn}}[k] = \min(50, \max(-20, d_T^{(4)}[k])) \quad (35)$$

$$d_R^{\text{syn}}[k] = \max(0, d_R^{(4)}[k]) \quad (36)$$

193 for all $k \in \{0, \dots, K - 1\}$.

194 3.2. Extremity index

195 Extremity from precipitation:

$$\mathcal{E}_{\text{precip}} = 2|1 - s_S| \quad (37)$$

196 So, $s_S = 1$ is the threshold for a drought season vs. a wet season with $s_S < 1$
 197 indicating drought and $s_S > 1$ indicating wet.

198 Extremity from temperature:

$$\mathcal{E}_{\text{temp}} = \frac{|s_T|}{5} \quad (38)$$

199 indicating that $\pm 5^\circ\text{C}$ is the threshold for extreme/not extreme temperature.
 200 Extremity from a drought event:

$$\mathcal{E}_{\text{drought}} = \sum_{(k_0, \kappa, \ell) \in \mathcal{D}} \frac{\kappa}{500} \ell \quad (39)$$

201 indicating that 500 hours (21 days) constitutes the threshold for long vs.
 202 short drought.

Extremity from a heat wave or cold snap event:

$$\mathcal{E}_{\text{heat}} = \sum_{(k_0, \kappa, \ell) \in \mathcal{H}} \frac{\kappa}{200} \frac{\ell}{5} \quad (40)$$

$$\mathcal{E}_{\text{cold}} = \sum_{(k_0, \kappa, \ell) \in \mathcal{C}} \frac{\kappa}{200} \frac{\ell}{5} \quad (41)$$

203 indicating that a long heat wave or cold snap is considered to be > 500 hours
 204 and temperatures are considered to be extreme if 5°C higher or lower than
 205 typical.

206 The aggregate extremity score is then

$$\mathcal{E} = \mathcal{E}_{\text{precip}} + \mathcal{E}_{\text{temp}} + \mathcal{E}_{\text{drought}} + \mathcal{E}_{\text{heat}} + \mathcal{E}_{\text{cold}} \quad (42)$$

207 4. Model predictive control

208 4.1. Constrained finite-time optimal control

209 At each decision epoch, model predictive control (MPC) solves a con-
 210 strained finite-time optimal control (CFTOC) problem over a planning hori-
 211 zon of K_d days. Discrete-time optimal control is concerned with choosing an
 212 optimal input sequence over the horizon K_d

$$\mathcal{U}_{0 \rightarrow K_d} = \{u[k]\} \quad \text{for } k = 0, \dots, K_d - 1 \quad (43)$$

213 with respect to some objective function over a finite or infinite time horizon
 214 in order to apply it to a system with a given initial state $x[0]$. The objective
 215 function is often defined as a sum of stage costs $q(x[k], u[k])$ and when the
 216 horizon has finite length, a terminal cost $p(x[K_d])$. That is

$$J_{0 \rightarrow K_d}(x[0], \mathcal{U}_{0 \rightarrow K_d}) = p(x[K_d]) + \sum_{n=0}^{K_d-1} q(x[n], u[n]) \quad (44)$$

217 where the states $\mathcal{X}_{0 \rightarrow K_d} = \{x[k]\}$ for $k = 0, \dots, K_d - 1$ must satisfy the
 218 initial condition and system dynamics

$$\begin{cases} x[0] = x_0 \\ x[k+1] = g(x[k], u[k]) \end{cases} \text{ for } k = 0, \dots, K_d - 1 \quad (45)$$

219 and there may be other state or input constraints formulated as inequalities

$$h(x[k], u[k]) \leq 0 \text{ for } k = 0, \dots, K_d - 1 \quad (46)$$

220 In the finite horizon case, there may also be a terminal constraint requiring
 221 the final state to lie in some terminal set $x[K] \in \mathcal{X}_{\text{final}}$.

222 In our specific case, we construct the problem as a minimization

$$\begin{aligned} J_{0 \rightarrow K_d}^*(x[0]) &= \min_{\mathcal{U}_{0 \rightarrow K_d}} J_{0 \rightarrow K_d}(x[0], \mathcal{U}_{0 \rightarrow K_d}) \quad \text{s.t.} \\ &\begin{cases} x[0] = x_0 \\ x[k+1] = g(x[k], u[k]) \text{ for } k = 0, \dots, K_d - 1 \\ x \in \mathbb{R}^+ \\ u \in \mathcal{U} \end{cases} \end{aligned} \quad (47)$$

223 where the stage cost penalizes input usage and nutrient anomalies:

$$q(x[k], u[k]) = \omega_w \left(\frac{u_w[k]}{u_{w,\text{typ}}} \right)^2 + \omega_f \left(\frac{u_f[k]}{u_{f,\text{typ}}} \right)^2 + \omega_{\Delta w} (\Delta_w[k])^2 + \omega_{\Delta f} (\Delta_f[k])^2 \quad (48)$$

224 Here ω_w and ω_f are weights on normalized irrigation and fertilizer inputs,
 225 $u_{w,\text{typ}}$ and $u_{f,\text{typ}}$ are typical application rates, and $\omega_{\Delta w}$ and $\omega_{\Delta f}$ penalize the
 226 cumulative nutrient anomalies Δ_w and Δ_f defined in (5). The terminal cost
 227 rewards crop development:

$$p(x[K_d]) = -\omega_h \frac{x_h[K_d]}{k_h} - \omega_A \frac{x_A[K_d]}{k_A} - \omega_P \frac{x_P[K_d]}{k_P} \quad (49)$$

where ω_h , ω_A , and ω_P weight the normalized final height, leaf area, and fruit biomass, respectively. There is no terminal set constraint because we want the plant to grow as much as possible. The terms in the stage cost have been squared in order to encourage sparsity in actuation, more similar to what a farmer might actually implement.

4.2. Solution method

The CFTOC problem is formulated in Pyomo [10] and solved using the IPOPT interior-point nonlinear optimizer [11] with the MUMPS linear solver. The nonlinearity arises from the logistic dynamics, FIR convolution, EMA filtering, and exponential nutrient factor computation. We use an adaptive barrier parameter strategy for robust convergence.

4.3. Receding-horizon algorithm

MPC implements the CFTOC in a receding-horizon fashion, re-optimizing daily based on updated state and weather observations. Let k index the decision day, and let $u[k] = (u_w[k], u_f[k])$ denote the daily irrigation and fertilizer rates. Let $\hat{d}_S, \hat{d}_T, \hat{d}_R$ denote forecast weather and d_S, d_T, d_R denote actual observed weather (precipitation, temperature, radiation).

Algorithm 1 presents the MPC procedure. At each decision day k :

1. Observe current plant state $x[k]$ and obtain K_d -day weather forecast $\{(\hat{d}_S, \hat{d}_T, \hat{d}_R)_{k+i}\}_{i=0}^{K_d-1}$.
2. Solve the CFTOC problem (47) to obtain optimal control sequence $\{u^*[k+j]\}_{j=0}^{K_d-1}$.
3. Apply only the first control $u^*[k] = (u_w[k], u_f[k])$ as constant rates over day k .
4. Simulate hourly plant dynamics over the day using actual (not forecast) weather.
5. Advance to day $k+1$ and repeat.

4.4. Feedback properties

The key advantage of MPC over open-loop optimization (such as GA) is its closed-loop nature. By re-solving the optimization problem each day with updated state and weather information, MPC can:

- **Correct for forecast errors:** If yesterday's weather differed from the forecast, today's optimization accounts for the actual plant state.

Algorithm 1 Model Predictive Control for Irrigation and Fertilization

```
1: Input: Initial state  $x[0]$ , horizon  $K_d$ , season length  $K$  days, weather
   data
2: Output: Control history  $\{u[k]\}_{k=0}^{K-1}$ , final state  $x[K]$ 
3:
4: Initialize FIR kernel buffers, EMA state variables
5: for  $k = 0$  to  $K - 1$  do
6:   Aggregate hourly weather forecast into daily averages for days
      $k, \dots, k + K_d - 1$ 
7:   Solve CFTOC( $x[k], \{(\hat{d}_S, \hat{d}_T, \hat{d}_R)_{k+i}\}_{i=0}^{K_d-1}$ )  $\rightarrow \{u^*[k+i]\}_{i=0}^{K_d-1}$ 
8:   Extract first control:  $(u_w[k], u_f[k]) \leftarrow u^*[k]$ 
9:   for  $t = 0$  to  $23$  do ▷ Hourly simulation within day  $k$ 
10:    Apply  $(u_w[k], u_f[k])$  with actual weather
         $(d_{S,24k+t}, d_{T,24k+t}, d_{R,24k+t})$ 
11:    Update FIR buffers, EMA states, nutrient factors
12:    Advance plant state using closed-form logistic solution (2)
13:   end for
14:    $x_{k+1} \leftarrow$  current plant state
15: end for
16: return  $\{u[k]\}_{k=0}^{K-1}, x[K_d]$ 
```

- 261 • **Adapt to changing conditions:** If a heat wave arrives unexpectedly,
262 MPC can adjust irrigation to maintain nutrient factors.
- 263 • **Exploit updated forecasts:** Longer-range forecasts become more
264 accurate as the event approaches.

265 This adaptivity comes at computational cost—solving a nonlinear opti-
266 mization problem each day—but modern solvers handle the problem scale (5
267 state variables, 2 controls, 9-day horizon) in under one second per solve.

268 5. Bayesian optimization for MPC parameter tuning

269 The MPC cost function contains seven tunable weights: $\omega_w, \omega_f, \omega_{\Delta w}, \omega_{\Delta f}, \omega_h, \omega_A, \omega_P$,
270 plus the horizon length H . These parameters significantly affect controller
271 behavior, and their optimal values depend on the weather scenario ensemble.
272 We use Bayesian Optimization (BO) to automatically tune these parameters
273 for robust performance.

274 *5.1. Bayesian optimization overview*

275 Standard Gaussian Process (GP) Bayesian Optimization models the ob-
 276 jective function as a GP:

$$f(x) \sim \mathcal{GP}(m(x), g(x, x')) \quad (50)$$

277 where x represents hyperparameter candidates and $f(x)$ is the performance
 278 metric. Given observations \mathcal{D}_n , the posterior

$$p(f(x)|\mathcal{D}_n) \sim \mathcal{N}(\boldsymbol{\mu}(\mathbf{x}), \boldsymbol{\sigma}_n^2(\mathbf{x})) \quad (51)$$

279 provides mean and uncertainty estimates that guide acquisition. The next
 280 sample is chosen by maximizing an acquisition function:

$$x_{n+1} = \arg \max_x \mathbb{E}(\mu(x), \sigma(x)) \quad (52)$$

281 balancing exploration (high uncertainty) against exploitation (high predicted
 282 value).

283 Tree-structured Parzen Estimation (TPE) takes an alternative approach:
 284 rather than modeling $p(y|x)$ directly, TPE models the inverse $p(x|y)$ using
 285 two density functions. Observations are partitioned by a quantile threshold γ
 286 (typically 0.1–0.25) into “good” and “bad” sets, with corresponding densities
 287 $l(x) = p(x|y \leq y^-)$ and $g(x) = p(x|y > y^-)$, where y^- satisfies

$$P(y \leq y^-) = \gamma, \quad \gamma \in (0, 1) \quad (53)$$

288 To derive the TPE acquisition function, we begin with expected improve-
 289 ment for minimization:

$$\mathbb{E}[I(x)] = \int_{-\infty}^{y^-} (y^- - y) p(y|x) dy \quad (54)$$

290 Applying Bayes’ rule $p(y|x) = p(x|y)p(y)/p(x)$:

$$\mathbb{E}[I(x)] = \int_{-\infty}^{y^-} (y^- - y) \frac{p(x|y)p(y)}{p(x)} dy \quad (55)$$

291 Under the TPE assumption that $p(x|y) \approx l(x)$ for $y \leq y^-$:

$$\mathbb{E}[I(x)] = \frac{l(x)}{p(x)} \int_{-\infty}^{y^-} (y^- - y) p(y) dy \quad (56)$$

292 Since the integral is constant with respect to x :

$$\mathbb{E}[I(x)] \propto \frac{l(x)}{p(x)} \quad (57)$$

293 Expanding $p(x)$ via the law of total probability:

$$p(x) = \gamma l(x) + (1 - \gamma)g(x) \quad (58)$$

294 yields:

$$\mathbb{E}[I(x)] \propto \frac{l(x)}{\gamma l(x) + (1 - \gamma)g(x)} \quad (59)$$

295 For fixed γ , maximizing expected improvement is equivalent to maximizing
296 $l(x)/g(x)$, which serves as the TPE acquisition function.

297 TPE offers computational advantages over GP-based methods and han-
298 dles mixed parameter spaces (continuous, discrete, categorical) naturally.
299 These properties make TPE well-suited for MPC parameter tuning, where
300 the objective landscape may contain discontinuities from solver failures and
301 the search space includes both continuous weights and integer horizon length.

302 5.2. Kernel density estimation

303 TPE approximates the densities $l(x)$ and $g(x)$ using kernel density esti-
304 mation (KDE). Given samples $\{x_i\}_{i=1}^n$, the kernel density estimator is:

$$\hat{p}(x) = \frac{1}{n} \sum_{i=1}^n g(x, x') \quad (60)$$

305 with Gaussian kernel $g(x, x') = \mathcal{N}(x|x', h^2)$ and bandwidth h . In one dimen-
306 sion:

$$\hat{p}(x) = \frac{1}{n} \sum_{i=1}^n \frac{1}{\sqrt{2\pi}h} \exp\left\{-\frac{1}{2} \frac{(x - x')^2}{h^2}\right\} \quad (61)$$

307 For multivariate parameters, TPE assumes independence across dimen-
308 sions (naive Bayes):

$$l(x) \approx \prod_{j=1}^d l_j(x_j) \quad \text{and} \quad g(x) \approx \prod_{j=1}^d g_j(x_j) \quad (62)$$

309 Rather than optimizing $l(x)/g(x)$ directly, TPE samples candidates from $l(x)$
310 and selects the one maximizing $l(x)/g(x)$.

311 The “tree-structured” aspect of TPE accommodates conditional param-
312 eter dependencies—where some parameters are only relevant given certain
313 values of others—by modeling the joint distribution as:

$$p(x) = p(x_1)p(x_2|x_1)p(x_3|x_1, x_2)\dots \quad (63)$$

314 5.3. Search space

315 Table 1 defines the search space for MPC parameter tuning. Cost weights
 316 use log-scale sampling to span multiple orders of magnitude, while value
 317 weights and horizon use linear/integer sampling.

Parameter	Lower	Upper	Scale
ω_w (irrigation cost)	0.001	10.0	log
ω_f (fertilizer cost)	0.0001	1.0	log
$\omega_{\Delta w}$ (water anomaly)	0.001	10.0	log
$\omega_{\Delta f}$ (fertilizer anomaly)	0.001	10.0	log
ω_h (height value)	10.0	1000.0	linear
ω_A (leaf area value)	10.0	1000.0	linear
ω_P (fruit biomass value)	100.0	10000.0	linear
H (horizon, days)	3	14	integer

Table 1: Bayesian optimization search space for MPC parameters.

318 5.4. Robust optimization objective

319 For robust parameter tuning, we optimize average performance across
 320 multiple weather scenarios:

$$\boldsymbol{\theta}^* = \arg \max_{\boldsymbol{\theta}} \frac{1}{|\mathcal{S}|} \sum_{\mathcal{S}_i \in \mathcal{S}} \text{Revenue}(\text{MPC}(\boldsymbol{\theta}, \mathcal{S}_i)) \quad (64)$$

321 where \mathcal{S} is a representative subset of weather scenarios. This encourages
 322 parameters that perform well across diverse conditions rather than overfitting
 323 to a single scenario.

324 5.5. TPE algorithm

325 Algorithm 2 presents the TPE-based parameter tuning procedure. The
 326 objective function averages MPC performance across multiple weather sce-
 327 narios, encouraging parameters that perform well across diverse conditions
 328 rather than overfitting to a single scenario.

329 We use $N = 100$ trials with $N_0 = 20$ random startup trials before en-
 330 gaging the TPE sampler. For robust optimization, we use a representative
 331 subset of 5 scenarios spanning the extremity range.

Algorithm 2 Bayesian Optimization for MPC Parameter Tuning

```
1: Input: Search space  $\Theta$  (Table 1), weather scenarios  $\mathcal{S}$ , budget  $N$ , startup  
   trials  $N_0$   
2: Output: Optimal parameters  $\theta^*$   
3:  
4: Initialize TPE surrogate model  
5: for  $n = 1$  to  $N$  do  
6:   if  $n \leq N_0$  then  
7:      $\theta_n \leftarrow$  sample uniformly from  $\Theta$   
8:   else  
9:      $\theta_n \leftarrow \arg \max_{\theta} \text{EI}(\theta)$  using TPE  
10:  end if  
11:  
12:   $r_n \leftarrow 0$   
13:  for each scenario  $\mathcal{S}_i \in \mathcal{S}$  do  
14:    Run MPC with parameters  $\theta_n$  on scenario  $\mathcal{S}_i$   
15:     $r_n \leftarrow r_n + \text{Revenue}_i / |\mathcal{S}|$   
16:  end for  
17:  Update TPE model with observation  $(\theta_n, r_n)$   
18: end for  
19:  
20:  $\theta^* \leftarrow \arg \max_n r_n$   
21: return  $\theta^*$ 
```

332 6. Case study: corn in iowa

333 We demonstrate the framework using corn, the most widely planted crop
334 in the United States with over 90 million acres harvested annually [12].
335 The case study uses historical weather data from Fairfax, Iowa (41.76°N,
336 91.87°W), a representative location in the Corn Belt (USDA climate zones
337 4b–5b).

338 6.1. Scenario configuration

339 The simulation covers a typical growing season from late April to early
340 October (approximately 2900 hours). Environmental inputs are:

- 341 • **Temperature and radiation:** Hourly data from NSRDB for Fairfax,
342 IA. Mean temperature is 22.8°C; mean solar radiation is 580 W/m².

- **Precipitation:** Daily data from NOAA, interpolated to hourly resolution.
- **Typical nutrient expectations:** Based on agronomic recommendations [13], the model expects 28 inches of water and 355 lbs of NPK fertilizer over the season ($w_{\text{typ}} \approx 0.01$ in/hr, $f_{\text{typ}} \approx 0.12$ lb/hr).

6.2. Three strategies for comparison

We compare three irrigation and fertilization strategies representing different approaches to resource management:

Farmer Baseline. Standard agronomic best practices based on published recommendations [14, 15]: weekly irrigation at 1 inch per application, and monthly fertilization at 90 lbs per application. This represents what a well-informed farmer might implement without optimization.

Fixed GA. A strategy optimized via genetic algorithm [6] for drought conditions (50% of normal precipitation). The GA searches over four parameters—irrigation frequency, irrigation amount, fertilizer frequency, and fertilizer amount—to maximize net revenue. The optimal strategy applies irrigation every 52 days at 5.0 inches per application, and fertilizer every 33 days at 77 lbs per application. This represents the best fixed strategy when drought is anticipated.

Adaptive MPC. Model Predictive Control that re-optimizes daily based on observed weather and current plant state. Unlike the fixed strategies, MPC adjusts resource allocation throughout the growing season in response to actual conditions.

Table 2 summarizes the control parameters for each strategy.

Strategy	Irrig. Freq. (days)	Irrig. Amt. (in)	Fert. Freq. (days)	Fert. Amt. (lbs)
Farmer Baseline	7	1.0	30	90
Fixed GA	52	5.0	33	77
Adaptive MPC	Daily re-opt.	Variable	Daily re-opt.	Variable

Table 2: Control parameters for the three strategies compared in this study.

6.3. MPC configuration

The MPC controller uses a 9-day planning horizon ($K_d = 9$) with daily re-optimization. Control bounds are set to $u_w \in [0, 0.7]$ inches/hour and $u_f \in [0, 12]$ lbs/hour, reflecting practical application rate limits.

371 MPC weight parameters were tuned using Bayesian optimization (100
372 trials) to maximize robust performance across 5 representative weather sce-
373 narios. The optimal parameters are:

- 374 • Input costs: $\omega_w = 0.177$ \$/inch, $\omega_f = 0.002$ \$/lb
- 375 • Anomaly penalties: $\omega_{\Delta w} = 2.94$, $\omega_{\Delta f} = 1.21$
- 376 • Value weights: $\omega_h = 590.8$ \$/m, $\omega_A = 491.0$ \$/m², $\omega_P = 1203.3$ \$/kg

377 Note that these weights differ from the economic weights used in the
378 GA cost function; they are tuned to optimize MPC behavior rather than
379 represent true economic values.

380 6.4. Weather scenario suite

381 We evaluate both GA and MPC across 21 stochastic weather scenarios
382 generated from the baseline historical data. Table 3 summarizes the scenario
383 categories.

Category	Count	Extremity Range
Normal	5	0.03–0.18
Moderate	5	0.35–0.90
Drought	4	1.20–2.45
Wet/Cool	2	0.95–1.10
Heat Stress	2	2.10–3.50
Extreme	2	5.60–8.38

Table 3: Weather scenario categories with extremity index ranges.

384 6.5. Results

385 Table 4 presents summary statistics for all three strategies across the
386 21 weather scenarios. Both optimization-based methods substantially out-
387 perform farmer baseline practices, with the Fixed GA achieving the highest
388 mean revenue and MPC achieving the lowest variance.

389 Both the Fixed GA and MPC outperform farmer baseline in all scenarios,
390 with mean advantages of \$170/acre and \$123/acre, respectively. When com-
391 paring GA to MPC directly, MPC wins in 12 of 21 scenarios, while GA wins
392 in the remaining 9. The key insight is *which* scenarios favor each strategy.

Strategy	Mean (\$/acre)	Std Dev	CV (%)	Min	Max
Farmer Baseline	626	135	21.6	385	853
Fixed GA	796	132	16.6	550	997
Adaptive MPC	750	115	15.4	445	886

Table 4: Summary statistics for the three strategies across 21 weather scenarios. CV = coefficient of variation (standard deviation / mean).

393 Table 5 presents results for representative scenarios spanning the ex-
394 tremity range. MPC outperforms GA in normal and wet conditions, where
395 the GA’s drought-optimized strategy applies more resources than necessary.
396 Conversely, GA outperforms MPC in drought scenarios, where its optimiza-
397 tion assumptions match actual conditions.

Scenario	Extremity	Farmer	Fixed GA	MPC	MPC–GA
normal_1 (baseline)	0.00	587	784	848	+64
moderate_wet	0.70	453	629	716	+87
moderate_dry	0.80	721	913	796	−116
wet_year	1.10	385	551	633	+82
mild_drought	1.30	853	997	717	−280
summer_drought	1.70	752	944	746	−197
heat_stress	1.70	669	855	795	−60
extreme_drought_heat	4.97	768	836	518	−317
worst_case	8.38	659	734	445	−289

Table 5: Revenue (\$/acre) for representative scenarios. MPC outperforms GA in normal/wet conditions; GA outperforms MPC in drought conditions.

398 Figure 1 visualizes revenue across all 21 scenarios, sorted by increasing
399 extremity index. The divergence between strategies is evident: MPC (green)
400 consistently outperforms in the left portion of the plot (normal conditions),
401 while Fixed GA (orange) dominates in the right portion (drought and ex-
402 treme conditions).

403 6.6. Performance by weather type

404 To better understand when each strategy excels, we categorize scenarios
405 by their dominant characteristic and compute mean revenue within each
406 category (Table 6).

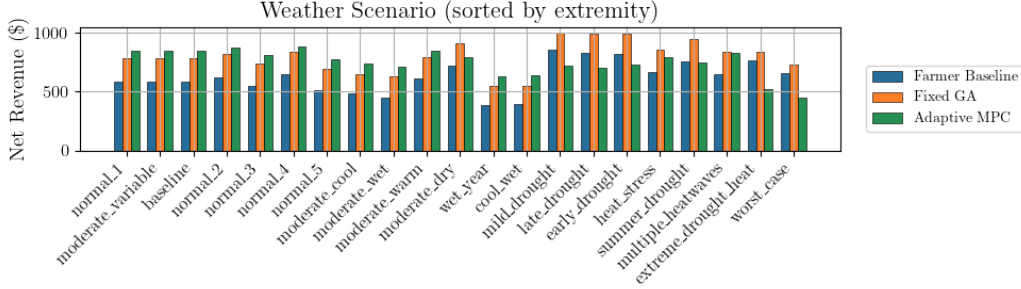


Figure 1: Revenue comparison across all 21 weather scenarios, sorted by extremity index. Farmer Baseline (blue), Fixed GA (orange), and Adaptive MPC (green). Both optimization-based methods outperform the baseline in all scenarios. MPC excels in normal/wet conditions (left), while Fixed GA excels in drought conditions (right).

Weather Type	n	Farmer	Fixed GA	MPC
Normal/Baseline	7	571	764	829
Wet/Cool	4	419	590	681
Drought	4	814	981	723
Heat Stress	4	685	851	762
Extreme Combined	2	713	785	482

Table 6: Mean revenue (\$/acre) by weather category. MPC excels in normal and wet conditions; GA excels in drought conditions.

407 The pattern is clear: MPC outperforms the Fixed GA by \$65/acre on average
408 in normal conditions and by \$91/acre in wet/cool conditions. However,
409 the Fixed GA outperforms MPC by \$258/acre in drought scenarios and by
410 \$303/acre in the most extreme combined scenarios. This divergence reflects
411 the fundamental difference in approach: the GA was optimized for drought
412 and performs best when those assumptions hold, while MPC adapts to ob-
413 served conditions but cannot anticipate future drought stress as effectively.
414 Figure 2 illustrates this pattern visually.

415 6.7. Variance and risk analysis

416 The coefficient of variation (CV), defined as the ratio of standard deviation
417 to mean, provides a normalized measure of consistency:

$$CV = \frac{\sigma}{\mu} \times 100\% \quad (65)$$

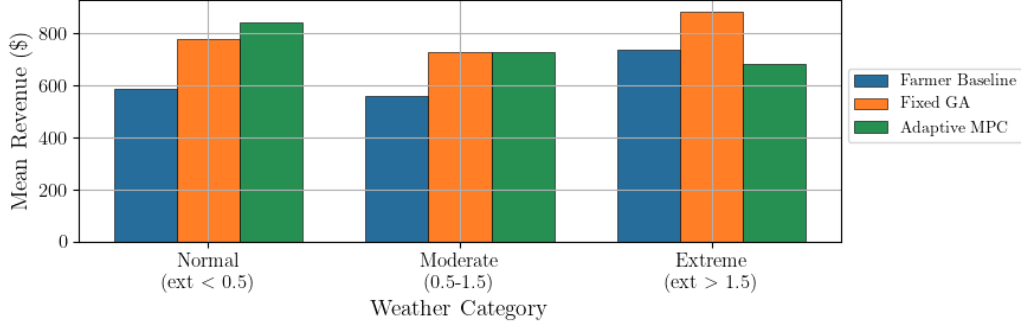


Figure 2: Mean revenue by weather category. MPC (green) outperforms Fixed GA (orange) in normal and moderate conditions, while Fixed GA dominates in drought and extreme scenarios. Both optimization methods substantially outperform Farmer Baseline (blue) across all categories.

418 As shown in Table 4, MPC achieves the lowest CV (15.4%) compared
 419 to the Fixed GA (16.6%) and Farmer Baseline (21.6%). This indicates that
 420 MPC delivers the most consistent relative performance across the diverse
 421 weather scenarios, even though its mean revenue is lower than the Fixed
 422 GA.

423 The risk-return tradeoff becomes apparent when examining the full dis-
 424 tribution. The Fixed GA achieves the highest maximum revenue (\$997/acre
 425 in mild drought) but also experiences larger swings: its revenue ranges from
 426 \$550 to \$997, a spread of \$447. MPC’s range is tighter at \$441 (\$445 to
 427 \$886), despite having a lower floor.

428 For risk-averse decision-makers, this tradeoff is significant. Consider a
 429 farmer who must meet fixed costs of \$600/acre. The Fixed GA falls below
 430 this threshold in 2 scenarios (wet_year and cool_wet), while MPC falls below
 431 in 3 scenarios (the same two plus worst_case). However, when conditions
 432 are uncertain—when the farmer cannot predict whether drought or flooding
 433 is more likely—MPC’s lower variance may be preferable because it reduces
 434 exposure to large deviations from expected performance.

435 Figure 3 shows the revenue distribution for each strategy as a box plot.
 436 The Fixed GA has the highest median and mean (red diamond), but also
 437 exhibits greater spread. MPC’s distribution is more compact, reflecting its
 438 consistent performance across diverse conditions.

439 Figure 4 directly compares the coefficient of variation for each strategy.
 440 MPC achieves a 7% reduction in relative variability compared to the Fixed

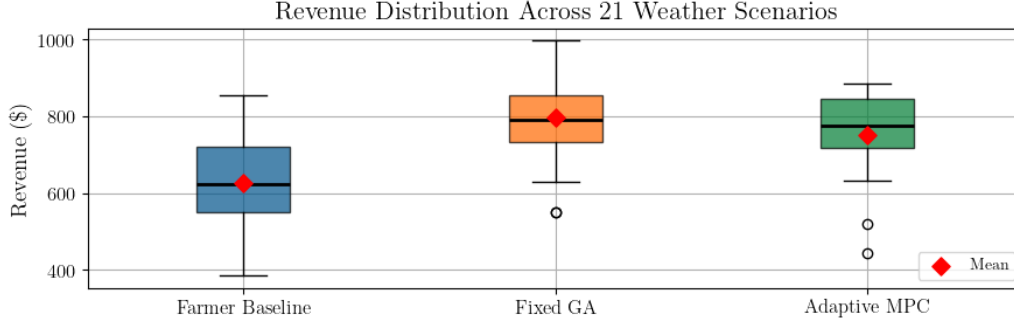


Figure 3: Revenue distribution across 21 weather scenarios. Box plots show median (black line), interquartile range (box), and full range (whiskers). Red diamonds indicate means. MPC exhibits the most compact distribution despite a lower mean, indicating more consistent performance.

GA (15.4% vs 16.6%), and a 29% reduction compared to Farmer Baseline (15.4% vs 21.6%). This consistency is a key advantage for operations that prioritize predictable outcomes over maximum expected returns.

6.8. Resource usage patterns

MPC’s adaptive nature is evident in its resource usage across scenarios. While GA applies the same total irrigation regardless of conditions, MPC irrigation varies from 3.9 inches (wettest scenario) to 6.3 inches (driest scenario). This adaptation allows MPC to conserve water when natural precipitation is sufficient while providing additional irrigation when stress threatens crop development.

7. Discussion

7.1. Interpretation of results

Our results reveal that the choice between fixed and adaptive strategies depends critically on the nature of weather uncertainty. This finding has important practical implications.

When fixed optimization excels. If climate trends are predictable—for example, if a region is experiencing increasing drought frequency due to climate change—then optimizing a fixed strategy for those expected conditions can be highly effective. In our study, the GA-optimized strategy

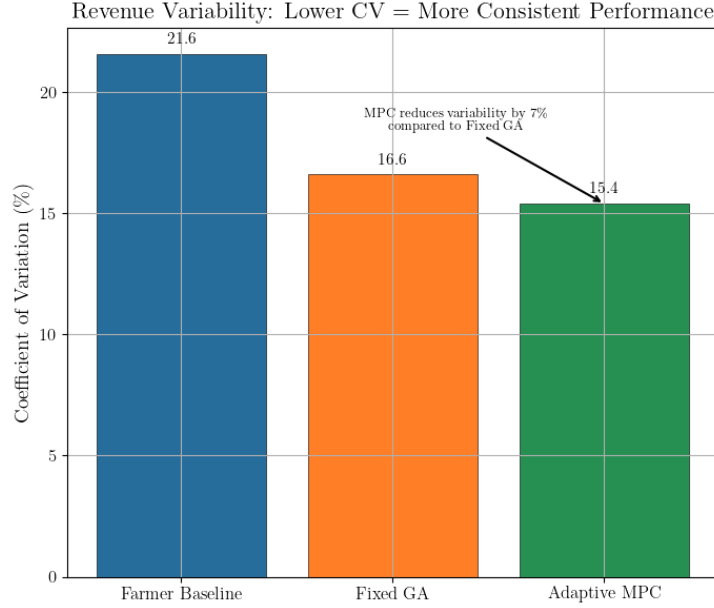


Figure 4: Coefficient of variation (CV) comparison. Lower CV indicates more consistent relative performance. MPC achieves the lowest CV (15.4%), followed by Fixed GA (16.6%) and Farmer Baseline (21.6%).

460 achieved \$997/acre under mild drought, the highest revenue of any strat-
 461 egy in any scenario. For farmers in regions where drought is the dominant
 462 concern, such a strategy may be optimal.

463 **When adaptive control excels.** If weather patterns are uncertain
 464 or variable—if both drought and flooding are plausible within the plan-
 465 ning horizon—then MPC provides valuable insurance. MPC achieved \$633–
 466 716/acre in wet conditions, compared to only \$550–630 for the Fixed GA.
 467 The GA’s drought-optimized parameters (infrequent, heavy irrigation) are
 468 poorly suited to wet conditions, where lighter, more frequent applications
 469 would be preferable.

470 **The value of adaptability.** MPC’s adaptive behavior is evident in
 471 its resource usage patterns. While the Fixed GA applies the same total
 472 irrigation in every scenario, MPC varies its irrigation from approximately 3.9
 473 inches in the wettest scenario to 6.3 inches in the driest. This responsiveness
 474 allows MPC to conserve resources when conditions are favorable and apply
 475 additional inputs when stress threatens crop development.

476 **Risk-return tradeoff.** The comparison reveals a classic risk-return

tradeoff. The Fixed GA maximizes expected revenue but with higher variance; MPC achieves lower expected revenue but with the most consistent performance (lowest CV). For operations with significant fixed costs or limited financial reserves, MPC’s consistency may be preferable despite the lower mean. For operations that can absorb year-to-year variability, the Fixed GA’s higher expected return may be more attractive.

7.2. Computational considerations

Each CFTOC solve requires approximately 0.5–1.0 seconds on a modern workstation using IPOPT. Over a 121-day growing season with daily re-optimization, total computation time is approximately 1–2 minutes.

The Bayesian optimization for parameter tuning requires 100 trials, each involving multiple full-season MPC simulations. Total tuning time is approximately 2–4 hours, but this is a one-time offline computation. Once parameters are tuned, MPC operates with minimal computational burden.

7.3. Limitations and extensions

Several limitations suggest directions for future work:

Perfect forecast assumption. Our MPC formulation assumes perfect weather forecasts over the planning horizon. In practice, forecast accuracy degrades with lead time. Incorporating forecast uncertainty through stochastic MPC or robust optimization would improve real-world applicability.

Single-point model. The crop model represents a single plant without spatial heterogeneity. Field-scale implementation would require accounting for spatial variation in soil properties, drainage, and microclimate.

Simplified economics. Our cost function uses constant economic weights. In practice, crop prices fluctuate seasonally, and input costs may have non-linear components (e.g., volume discounts, capacity constraints).

Daily control resolution. We optimize daily-average irrigation and fertilizer rates. Finer temporal resolution (e.g., hourly) could capture within-day dynamics but would substantially increase computational cost.

Additional control variables. The current formulation considers only irrigation and fertilizer. Other controllable factors—such as planting date, crop variety selection, or deficit irrigation strategies—could be incorporated into the optimization framework.

510 8. Conclusion

511 This paper presented a comparative study of fixed versus adaptive irri-
512 gation and fertilization strategies under weather uncertainty. We developed
513 an MPC framework with Bayesian-optimized parameters and evaluated it
514 against both farmer baseline practices and a GA-optimized fixed strategy
515 across 21 stochastic weather scenarios.

516 Our key findings are:

- 517 1. Both optimization-based methods (GA and MPC) substantially out-
518 perform farmer baseline practices, with mean advantages of \$170/acre
519 and \$123/acre, respectively.
- 520 2. The Fixed GA achieves the highest mean revenue (\$796/acre) but with
521 higher variance, while MPC achieves lower mean revenue (\$750/acre)
522 but with the lowest coefficient of variation (15.4% vs 16.6%).
- 523 3. MPC outperforms the Fixed GA in 12 of 21 scenarios—primarily in
524 normal and wet conditions—while the Fixed GA excels in drought sce-
525 narios for which it was optimized.
- 526 4. The choice between strategies involves a risk-return tradeoff: fixed op-
527 timization maximizes expected returns when conditions match assump-
528 tions; adaptive control provides consistency when weather is uncertain.

529 These findings have practical implications for agricultural decision-making.
530 In regions with predictable climate trends (e.g., increasing drought frequency),
531 optimizing a fixed strategy for those expected conditions can be highly effec-
532 tive. In regions with variable or uncertain weather patterns, adaptive MPC
533 provides valuable risk reduction through consistent performance.

534 The computational overhead of MPC is modest—daily optimization solves
535 complete in under one second—making real-time implementation feasible.
536 The framework is generalizable to other crops through re-parameterization
537 of the underlying growth model.

538 Future work will incorporate forecast uncertainty through stochastic MPC,
539 extend to field-scale spatial heterogeneity, and validate against field trial
540 data. Additionally, exploring hybrid strategies that combine fixed optimiza-
541 tion with adaptive adjustments may capture benefits of both approaches.

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Declarations

Competing Interests 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.

Code availability The source code used for this study is archived on Zenodo at <https://doi.org/10.5281/zenodo.18204023>.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process During the preparation of this work the authors used ChatGPT and Claude Code in order to generate some portions of the code base, though no underlying theory, and refine the original drafts of the paper. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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