Profitable Control in Agriculture

An Economic Framework for AI-Enabled Environmental Control

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Abstract

Agricultural technology increasingly makes temperature, humidity, light, irrigation, carbon dioxide, airflow, and other production variables technically controllable. Yet technical controllability is not the same as economic desirability. Each additional layer of control can raise yield, quality, timing reliability, or loss avoidance while also adding capital, energy, maintenance, sensing, integration, and management costs. This paper develops the Profitable Control framework by formalizing the argument in Kao (2026a) that the relevant question is not whether a variable can be controlled, but whether it is worth paying to control. The framework treats control as an economic choice over intensity rather than a binary technological capability.

The paper connects greenhouse optimal-control research, controlled-environment agriculture, vertical-farming economics, techno-economic benchmarking, and recent work on AI-enabled climate control. Existing studies already optimize yield, energy use, profit, and resource efficiency within particular systems. The contribution here is integrative rather than a claim to a new control-theoretic method: it introduces a portable vocabulary for comparing control decisions across crops, technologies, and locations. Four concepts organize the framework: Control Value, Control Burden, Profitable Control, and the Economic Control Boundary. A lightweight formulation states that tighter control is justified only when its expected incremental economic value exceeds its full incremental control burden.

Recent evidence illustrates why this distinction matters. Autonomous greenhouse systems can choose among very different lighting, heating, carbon-dioxide, irrigation, and harvest strategies while being judged on profit rather than biological output alone. Model-predictive control can materially reduce energy use and improve economic performance without necessarily making an otherwise unattractive production system viable. Vertical-farm studies likewise show that optimal settings depend on electricity prices, climate, crop physiology, capital structure, and the value of the crop being sold. The central implication is that AI does not repeal the economics of physical control. Its value lies in shifting the cost-value relationship of control: using existing equipment more selectively, responding to changing prices and crop states, and concentrating precision where the crop can pay for it.

Keywords: profitable control; agricultural AI; controlled environment agriculture; greenhouse climate control; vertical farming; economic optimization; model predictive control; agricultural technology

1. Introduction

Agriculture has always purchased control over nature. Irrigation reduces dependence on rainfall. Greenhouses reduce exposure to wind and temperature swings. Heating, ventilation, lighting, carbon-dioxide enrichment, dehumidification, fertigation, and increasingly sophisticated sensing systems move production further from uncontrolled environmental variation. In technical terms, the direction is straightforward: more infrastructure and better decision systems allow more variables to be measured and manipulated.

The economic direction is not straightforward. Nature is unreliable, but it also supplies services without appearing on the farm's electricity bill. Sunlight, ambient air movement, rainfall, and suitable seasonal temperatures may be inconsistent, but replacing them with engineered alternatives creates capital and operating costs. A farm can therefore become more technically controlled while becoming less economically attractive. The failure mode is not necessarily poor engineering. It can be successful engineering applied beyond the point at which the crop can pay for it.

Kao (2026a) frames this distinction as profitable control rather than maximum control: the objective is to control the variables that generate enough economic value to justify their cost. The source argument is deliberately simple. This paper formalizes it into a general decision framework and places it in conversation with greenhouse optimal control, controlled-environment agriculture (CEA), vertical-farming economics, and AI-enabled climate management.

The research question is: when does additional environmental control create economic value in agriculture, and where is the point beyond which tighter control costs more than it contributes? The question matters because modern agricultural AI can alter both sides of the answer. Better sensing and prediction can increase the value obtained from a given actuator. Dynamic optimization can reduce unnecessary heating, lighting, irrigation, or carbon-dioxide use. At the same time, AI can require new sensors, connectivity, software, integration, and operational capabilities. The relevant comparison is therefore not 'AI versus no AI' or 'high-tech versus low-tech.' It is the incremental value of a particular control capability relative to its full incremental burden.

The paper makes three contributions. First, it separates Control Value from Control Burden so that agronomic improvement is not treated as equivalent to economic improvement. Second, it defines the Economic Control Boundary as the locally optimal extent of control under crop, price, climate, and technology conditions. Third, it explains how AI can shift that boundary without assuming that greater automation or precision is always valuable. This is a conceptual framework, not a calibrated production model, and its purpose is to make cross-system comparisons and empirical tests easier.

2. Related Literature and the Economic Gap

2.1 Greenhouse optimal control already contains an economic logic

Greenhouse-control research has long recognized that a biologically ideal environment is not necessarily the economically optimal one. Van Straten and van Henten (2010) distinguish operational climate control from the broader economic optimization of greenhouse cultivation and argue for integrated control across tactical and operational timescales. Later reviews show how heating, ventilation, humidity, carbon dioxide, lighting, sensing, and crop dynamics interact in energy-intensive greenhouse systems (Iddio et al., 2020). More recent work explicitly balances predicted crop performance against energy use. Wang et al. (2023), for example, construct a multi-objective optimization problem that trades off predicted photosynthetic performance and power consumption rather than maximizing the crop response in isolation.

Economic objectives are also moving directly into model-predictive control. García-Mañas et al. (2024) formulate greenhouse production control around profit under uncertain market prices. Sooderjani et al. (2025) show in a vertical-farm setting that model-predictive control can reduce energy use and improve profitability relative to more conventional control while the overall production case can still remain economically unattractive. These studies are important because they demonstrate that control quality and system viability are distinct outcomes.

2.2 Controlled-environment agriculture makes the cost of control visible

CEA and vertical farming provide an unusually clear setting in which to observe the economics of control because many environmental services that are partly supplied by nature outdoors must be purchased explicitly indoors. Graamans et al. (2018) show that plant factories can achieve strong water, land, and carbon-dioxide productivity while using substantially more purchased energy than greenhouses because sunlight must be replaced. Van Delden et al. (2021) similarly identify profitability and energy efficiency as central constraints on scaling vertical farming. A systematic scoping review by Dsouza et al. (2023) finds that CEA research remains weighted toward technical and biological questions relative to socio-economic analysis, reinforcing the need to connect control performance to economic outcomes.

Recent techno-economic studies sharpen that connection. Arcasi et al. (2024) show that the energy cost of vertical-farm production varies materially with climate, lighting efficiency, intensity, and target temperature. Hopwood et al. (2024) demonstrate that greenhouse technology level does not map monotonically into economic performance: in a hot-humid case, a mid-tech configuration can perform worse financially than both lower- and higher-technology alternatives because of the interaction among capital cost, cooling performance, yield, and market conditions. The USDA's recent assessment likewise emphasizes that CEA opportunities coexist with substantial technical and economic challenges and that crop selection, facility design, energy use, and market conditions matter jointly (Dohlman et al., 2024).

2.3 Dynamic control changes the optimum rather than eliminating trade-offs

AI and dynamic control matter because the economically preferred setting is rarely constant. Kaiser et al. (2024) argue that vertical-farm setpoints should respond to changing plant physiology and electricity prices rather than remain fixed throughout production. The 2024 Autonomous Greenhouse Challenge makes this logic especially visible: teams controlled lighting, heating, carbon dioxide, water, plant density, and harvest timing, but the principal competition criterion was net profit, with resource and depreciation costs explicitly counted by the organizers (Wageningen University & Research, 2025). Different control strategies could produce successful crops, yet they generated different economic outcomes.

The newest vertical-farming literature further shows that control effectiveness depends on biological and economic constraints. Miserocchi and Franco (2025) benchmark current and prospective energy efficiency and find that physical crop requirements continue to set meaningful limits even as equipment improves. Ceccanti et al. (2026) model the joint effects of light, temperature, carbon dioxide, energy, water, cost, and carbon and identify settings that minimize production cost rather than simply maximize yield. Meeuws et al. (2026) show that increasing controllable inputs can shift crops from source limitation toward sink limitation, meaning that further control of the original variable can lose leverage once a different biological constraint becomes binding.

The literature therefore contains the ingredients of profitable control, but usually inside system-specific optimization problems. The remaining gap is a portable economic abstraction that can be applied before choosing a particular algorithm or facility design: what value does tighter control create, what full burden does it impose, and at what point does additional control stop paying for itself?

Table 1. Adjacent literatures and the remaining economic-control question

Literature	Primary objective	What it establishes	Remaining question
Greenhouse optimal control	Choose climate and production actions over time.	Economic objectives can be integrated with crop and energy models.	How should control value and full control burden be compared across systems?
CEA / vertical-farm economics	Assess resource use, cost, and commercial viability.	Energy, capital, crop choice, and local conditions shape viability.	Which specific variables and control intensities are worth

			paying to control?
AI / dynamic climate control	Adapt decisions to crop state, weather, and prices.	Dynamic control can improve resource use and economic outcomes.	When does the added intelligence layer create more value than its enabling cost?
Techno-economic benchmarking	Compare facility designs and technology levels.	More technology does not guarantee better economics.	Where is the economic boundary beyond which tighter control destroys value?

3. The Profitable Control Framework

3.1 Control is an economic intensity, not a binary capability

Let x denote an environmental or operational variable that can be influenced by the farm, such as temperature, humidity, light, irrigation, carbon dioxide, airflow, or nutrient delivery. Let k represent the intensity of control applied to that variable in a specific production context. The scale of k is context-specific; it can represent tighter tolerances, more frequent intervention, greater actuator capacity, more sensing, or more dynamic adjustment. It is not intended as a universal physical unit comparable across variables.

The useful question is therefore not whether x is controllable. Modern agriculture can technically control many variables. The question is how much control is economically justified under the crop, location, price, climate, capital, and technology conditions facing the producer.

3.2 Definition 1 — Control Value

Control Value is the expected incremental economic benefit created by increasing control intensity over a production variable relative to a defined baseline. It can arise through higher yield, improved quality, better timing, lower biological loss, greater consistency, reduced labor or supervision, reduced input waste, or a price premium. Control Value is measured economically rather than technologically: a more stable temperature is valuable only through the outcomes that stability changes.

This definition prevents a common category error. An agronomic improvement can be real without being commercially large enough to justify the system that creates it. The crop response and the economic response therefore have to be linked rather than assumed to be identical.

3.3 Definition 2 — Control Burden

Control Burden is the full incremental resource and organizational cost required to impose and sustain a given level of control. It includes more than electricity. Depending on the system, the burden can include capital expenditure, financing, depreciation, sensors, actuators, connectivity, software, data infrastructure, integration, water, consumables, maintenance, calibration, labor, training, service, downtime risk, and management complexity.

The distinction matters because a control algorithm can reduce one operating cost while requiring an enabling architecture that is expensive to install or maintain. Likewise, a high-tech facility can reduce biological variability while increasing dependence on energy, sensors, connectivity, software, and integrated equipment. Control Burden therefore belongs to the entire deployed control capability, not only to the marginal electricity consumed by an actuator. It should also include expected disruption losses: the probability of sensing, connectivity, software, or equipment failure multiplied by the economic consequence of degraded control, downtime, recovery, or crop loss.

3.4 Definition 3 — Profitable Control

For a given production context, define the net economic contribution of control intensity k as the difference between Control Value and Control Burden.

3.5 Definition 4 — Economic Control Boundary

The Economic Control Boundary is the level of control intensity beyond which additional control is not expected to increase net economic value. In a smooth interior case, the boundary occurs where the marginal economic value of tighter control equals its marginal control burden. In practice, the boundary may be discontinuous because technologies are purchased in discrete units, biological thresholds exist, and market prices change.

The boundary is local rather than universal. A lighting intensity that is justified for a premium strawberry crop under low-cost renewable power may be uneconomic for lettuce under high electricity prices. A cooling system that is valuable in an extreme climate may have little value in a mild one. The same technology can therefore lie on different sides of the Economic Control Boundary in different farms.

3.6 Principle 1 — The Profitable Control Principle

The Profitable Control Principle states: increase control only while the expected incremental economic value of tighter control exceeds its full incremental burden. The principle does not require a farm to minimize technology or to accept avoidable variability. It requires the farm to justify precision economically rather than treating precision itself as the objective.

This formulation also clarifies the relationship with the Agricultural Viability Frontier. Profitable control can improve an already viable production configuration, but if it removes a binding environmental or operational constraint it can also change whether the configuration is viable at all (Kao, 2026b). The two frameworks ask different questions: the Agricultural Viability Frontier asks whether production crosses an economic viability boundary; Profitable Control asks how much control over a particular variable is worth purchasing.

3.7 Lightweight formalization

Let V(k) denote expected Control Value and C(k) denote expected Control Burden for a defined control decision in a specified production context. The net contribution of control is:

$$N(k)=V(k)-C(k)$$

A move from baseline control k0 to tighter control k1 is economically justified when the incremental value exceeds the incremental burden:

$$\Delta V>\Delta C$$

The Economic Control Boundary can be represented conceptually as the control intensity that maximizes net contribution:

$$k*\in arg\,max[V(k)-C(k)]$$

These relationships are conceptual rather than empirically calibrated. V and C can be uncertain, discontinuous, and multi-dimensional; the notation is meant to expose the economic comparison that an empirical implementation would need to estimate.

Table 2. Core objects in the Profitable Control framework

Object	Definition	Typical components	Decision implication
Control Value	Expected incremental economic	Yield, quality, timing, avoided	Agronomic improvement must

	benefit from tighter control.	loss, reliability, labor, price premium.	translate into economic value.
Control Burden	Full incremental cost of imposing and sustaining control.	CAPEX, energy, sensing, software, maintenance, integration, financing, complexity.	Count the enabling system, not only actuator energy.
Profitable Control	A control increase for which incremental value exceeds incremental burden.	Context-specific comparison of ΔV and ΔC.	More precision is justified only while it adds net value.
Economic Control Boundary	The locally optimal extent of control before marginal burden overtakes marginal value.	Crop, climate, prices, technology, capital, alternatives.	The same technology can be optimal in one farm and excessive in another.

4. How Control Creates and Destroys Economic Value

4.1 Yield is only one component of Control Value

The most obvious benefit of environmental control is yield. More favorable temperature, light, irrigation, or carbon-dioxide conditions can increase biomass or shorten crop cycles. But Control Value is broader than yield. Stable conditions can improve grade, reduce rejected product, make harvest timing more predictable, protect against extreme events, and support contracts that value reliability. In some systems, control can reduce labor or allow operators to manage more production with the same team.

This wider accounting is important because the variable that creates the most biological response is not necessarily the variable that creates the most economic response. A quality improvement can be worth more than additional kilograms if buyers pay for it; conversely, additional output can have little value if it enters a market with weak prices or if the farm cannot sell it.

4.2 Control Burden often rises faster near the extremes

Tighter control commonly becomes more expensive as the target moves farther from ambient conditions. Heating a greenhouse a few degrees may be inexpensive under one climate and costly under another. Removing the last portion of humidity, maintaining very narrow temperature bands, or fully replacing sunlight with artificial lighting can require disproportionate energy and equipment. The engineering problem becomes more difficult precisely where the desired environment is farthest from what nature provides for free.

This creates diminishing economic returns to control even when the biological relationship remains positive. The farm may benefit from moving from poor control to adequate control, yet lose money moving from adequate control to near-perfect control. Graamans et al. (2018), Stanghellini and Katzin (2024), and recent energy benchmarks illustrate the significance of purchased energy once production is moved into highly controlled environments.

4.3 Biological saturation can move the binding constraint

Control can also lose value because biological response saturates. Increasing one input eventually exposes a different constraint. Meeuws et al. (2026) show this explicitly in vertical-farm modeling: stronger source capacity through light can move production toward sink limitation, so further increases in the original input no longer translate proportionally into output. The relevant economic implication is general. Control should follow the current binding constraint rather than continue intensifying the variable that was previously important.

A control system that is technically capable of maintaining a higher setpoint may therefore need to choose not to use that capability. The value of intelligence lies partly in recognizing when the marginal response has changed.

4.4 Prices make the preferred setting dynamic

The Economic Control Boundary shifts with input and output prices. If electricity prices rise, a previously profitable lighting or heating strategy can cross into negative net value even though the crop's physiology has not changed. If crop prices or quality premiums rise, the reverse can occur. García-Mañas et al. (2024) make market-price uncertainty part of greenhouse control; Kaiser et al. (2024) similarly emphasize that electricity prices and crop state can change the preferred operating settings over short intervals. To represent this explicitly, let t index the operating state or decision interval. Net contribution then becomes:

$$N_t(k_t) = V_t(k_t) - C_t(k_t)$$

and the economically preferred control intensity becomes:

$$k_{t,opt} \in \arg\max_k N_t(k)$$

These expressions do not imply that farms should continuously re-optimize every setting. They make explicit that the value and burden of control can move with crop state, weather, energy prices, output prices, and other time-varying conditions.

This is one reason fixed agronomic setpoints can be economically inferior to dynamic ones. The target should reflect both crop state and the cost of producing the target condition.

5. What AI Changes

5.1 AI can lower the operating burden of a given control capability

AI can create value without adding a new physical actuator. A greenhouse may already have heaters, vents, pumps, screens, and irrigation equipment. Better forecasting, state estimation, anomaly detection, or model-predictive control can change when and how those devices are used. If the same physical system achieves comparable crop outcomes with less energy, water, carbon dioxide, or operator intervention, the Control Burden curve shifts downward.

Sooderjani et al. (2025) provide a useful example. In their modeled vertical-farm case, model-predictive control reduced energy consumption relative to conventional control and improved profitability, yet the production system remained economically infeasible. This is exactly the distinction the framework is designed to preserve: better control can improve economics without crossing the viability threshold.

5.2 AI can increase Control Value through timing and coordination

AI can also increase the value obtained from existing inputs by coordinating several variables rather than optimizing them independently. Temperature affects crop development and energy demand; light interacts with photosynthesis and crop stage; humidity changes transpiration and disease risk; carbon dioxide has value only when other conditions allow the crop to use it. Control decisions therefore interact.

The 2024 Autonomous Greenhouse Challenge illustrates this multi-variable problem. Competing algorithms selected lighting, heating, carbon dioxide, water, plant density, pest-management actions, and harvest timing, while the principal score incorporated net profit rather than yield alone (Wageningen University & Research, 2025). The winning strategy did not imply that maximum values for each environmental variable were optimal. It demonstrated that the system had to allocate control across variables under a common economic objective.

5.3 AI can also add a new control burden

The effect is not automatically favorable. AI-enabled control can require sensors, cameras, connectivity, computing, data management, software subscriptions, integration, calibration, cybersecurity, and specialized service. Importantly, Control Burden need not rise smoothly. Some control capabilities require lumpy enabling investments in sensor networks, control hardware, integration, commissioning, or specialist support before any incremental benefit can be realized. A farm can therefore occupy an awkward middle position: too technologically committed to retain the economics of a simpler system, yet not capable or large enough to generate sufficient value to amortize the fixed burden.

Hopwood et al. (2024) illustrate the broader point: in their hot-humid greenhouse benchmark, economic performance was non-monotonic across technology levels, with the intermediate configuration carrying substantial added investment without a commensurate gain in economic output. This does not imply that medium-technology systems are generally inferior; it shows why the cost path of control can contain discrete jumps rather than a smooth progression.

The economic case for agricultural AI should therefore compare the value of the decisions improved by AI with the full cost of making those decisions machine-mediated. This is especially important in agriculture because heterogeneous facilities, crops, climates, and equipment can make deployment less standardized than ordinary software.

6. Empirical Illustrations and Organizational Implications

The framework can be used to interpret several recent findings without claiming that those studies were designed to test it directly. Table 3 summarizes five examples.

First, the Autonomous Greenhouse Challenge demonstrates that autonomous control can be evaluated against profit after accounting for input and depreciation costs, not merely against crop yield. Second, model-predictive control in vertical farming shows that a superior controller can improve an uneconomic system without making it profitable. Third, greenhouse benchmarking in a hot-humid climate shows that technology level and economic performance are not monotonic: an intermediate configuration can be inferior when its capital and cooling burdens are not matched by enough output value. Fourth, vertical-farm energy and crop models show that local climate, electricity prices, physiological saturation, and crop choice materially alter the optimum. Fifth, CEA research as a whole remains technically rich but comparatively thin in socio-economic analysis, suggesting that more studies should report the economic consequences of control choices alongside biological outcomes.

For farm managers, this shifts technology evaluation from feature comparison toward control economics. A proposal for more sensors, tighter climate bands, or greater automation should identify which variable is being controlled, the baseline level of control, the economic channel through which tighter control creates value, the full enabling burden, and the conditions under which the result changes sign. For technology vendors, the same logic discourages selling precision as an abstract virtue. The strongest product case is one in which the customer can see why a specific control improvement is worth more than it costs in that production context.

For investors and policymakers, the framework also cautions against treating 'controlled environment agriculture' as one homogeneous technology category. Hopwood et al. (2024), Arcasi et al. (2024), Dohlman et al. (2024), and Ceccanti et al. (2026) all point toward location- and system-specific economics. More control may be justified where climate is extreme, water is scarce, supply reliability is valuable, or the crop carries sufficient margin. The same control architecture can be excessive where nature already provides the relevant service cheaply.

Table 3. Recent evidence interpreted through the Profitable Control framework

Evidence	Observed result	Framework interpretation	Caution
Autonomous Greenhouse Challenge (WUR, 2025)	Teams controlled multiple variables; winner determined primarily by net profit after costs.	Control should be coordinated under an economic objective, not maximal setpoints.	Competition conditions are simplified relative to commercial farming.
Vertical-farm MPC (Sooderjani et al., 2025)	Lower energy use and improved profitability versus PID, while modeled viability remained unattractive.	Lower energy use and better control improved economic outcomes, but did not make the modeled production system economically viable.	Model-based case; not a general commercial benchmark.
Hot-humid greenhouse benchmark (Hopwood et al., 2024)	Technology level and payback were non-monotonic across designs.	Non-monotonic economic performance is consistent with context-specific benefits and lumpy enabling burdens.	Results depend on climate, design, prices, and assumptions.
Vertical-farm crop economics (Meeuws et al., 2026)	Higher controllable inputs can expose new biological constraints.	Marginal Control Value can decline when the binding constraint moves.	Modeled performance targets are not realized commercial outcomes.
Indoor vertical-farm viability (Ceccanti et al., 2026)	Cost-optimal settings emerge from joint energy, crop, location, and input trade-offs.	The economically preferred configuration need not maximize agronomic performance.	Scenario model; crop and locality choices matter.

7. Research Agenda

The framework suggests a research agenda centered on estimating control-response economics rather than only engineering performance.

First, empirical studies should estimate variable-specific response curves that link control intensity to economically relevant outputs. For temperature, light, humidity, irrigation, and carbon dioxide, this means measuring not only yield but also quality, cycle time, loss rates, labor, energy, and realized selling price. The objective is to estimate where marginal value begins to flatten relative to marginal burden.

Second, experiments should compare agronomic and economic setpoints. A controller that maximizes photosynthesis, biomass, or environmental stability may not maximize profit. Randomized or quasi-experimental comparisons across facilities, production cycles, or pricing regimes could test whether economically optimized control sacrifices small amounts of biological performance in exchange for larger reductions in energy or capital use.

Third, future work should decompose the value of AI from the value of the physical control system. If an existing greenhouse already has adequate actuators, the incremental contribution of AI may be primarily timing and coordination. In a new facility, by contrast, AI may be inseparable from sensors, actuators, and integration. Separating these components would make technology ROI more interpretable. Studies should also price management complexity directly rather than treating it as a residual. Useful proxies include training and onboarding hours, manual overrides, alarms requiring expert review, troubleshooting incidents, specialist-support time, unplanned downtime, mean time to diagnose, and mean time to recover. These can be translated into annualized labor, service, and interruption costs at the production-unit level rather than collapsed into an arbitrary complexity score.

Fourth, studies should model uncertainty explicitly. Weather, energy prices, crop prices, equipment failure, disease, and model error all affect the Economic Control Boundary. Stochastic control work such as García-Mañas et al. (2024) provides a natural starting point, but the empirical question is broader: how much option value comes from a control system that can adapt when conditions change, and how much should a farm pay for that flexibility?

Fifth, research should examine whether control decisions that are privately profitable are socially desirable. Energy- and carbon-intensive control can be rational for an individual producer while imposing environmental costs not fully reflected in private prices. Conversely, resilience, water savings, reduced pesticide use, or local supply continuity may create benefits that the farm cannot fully capture. Extending the framework from private Control Value and Control Burden to social value would make those trade-offs explicit rather than treating profitability as a complete welfare criterion.

8. Limitations

The Profitable Control framework is conceptual and deliberately lightweight. It does not provide a universal numerical scale for control intensity, and it should not be interpreted as an empirically calibrated production function. Different variables have different physical units, response times, and technical constraints. The notation is intended to discipline comparison, not to imply that temperature control and irrigation control can be placed on a single cardinal scale.

The framework also simplifies interactions among control variables. In real farms, temperature, humidity, light, water, nutrients, carbon dioxide, plant density, and labor decisions can be complements or substitutes. A change in one variable can alter the marginal value of another. The appropriate empirical implementation may therefore require multivariate optimization rather than separate one-variable curves.

The current evidence base is also concentrated in greenhouses, vertical farms, and other forms of controlled-environment agriculture. That concentration is useful because control costs are highly visible in these systems, but it limits generalization to open-field agriculture, livestock, aquaculture, and perennial crops. The framework should be tested in those settings rather than assumed to transfer unchanged.

Finally, private profitability does not equal social desirability. Carbon emissions, water scarcity, land use, food-system resilience, and other externalities can move in different directions. A privately profitable control system may still impose environmental costs, while a socially valuable control capability may not be privately financeable. The framework can incorporate those effects only when they are explicitly added to the value and burden terms.

9. Conclusion

Agriculture is entering a period in which more of the production environment can be measured, predicted, and controlled. The central economic problem is therefore shifting. Scarcity is no longer only a lack of technical capability; it is also the need to decide which capabilities are worth buying and using.

The Profitable Control framework formalizes a simple rule: control has value when the economic benefit of tighter control exceeds its full incremental burden. Control Value captures yield, quality, reliability, timing, avoided loss, labor, and other monetizable benefits. Control Burden captures energy, capital, sensing, integration, maintenance, financing, and organizational costs. Their relationship defines an Economic Control Boundary that changes with crop biology, local climate, energy prices, market prices, and technology.

AI matters because it can shift that boundary. Better decisions can reduce unnecessary energy use, coordinate multiple variables, respond to changing prices, and extract more value from equipment already in place. But AI cannot make physical inputs free or guarantee that a highly controlled production system is economically viable. The most advanced farm is therefore not necessarily the farm with the most control. The economically stronger farm is the one that knows where additional control still pays.

AI Use Disclosure

OpenAI's ChatGPT was used only for literature discovery and bibliographic verification. The author independently reviewed all cited sources and remains solely responsible for the final manuscript, its arguments, source selection, and citations.

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