

Eliminating Transboundary Haze via Agentic AI and Microalgae Bio-Refineries: The Eagor-Core Framework for Palm Oil Estate Transformation

Lanz CWJ Chan

Finamatrix Quant-Lab, Singapore

E-mail: lanz@finamatrix.net

Shin-Hung Pan

Department of Information Management,

Chaoyang University of Technology, Taiwan

**Corresponding author* Email: vincentpan@cyut.edu.tw

Published on October 15, 2026

Abstract

Transboundary haze in Southeast Asia persists because fire remains the cheapest way to clear and prepare land on tropical peat, while the health and climate costs of burning fall on others. This short paper asks whether an alternative revenue stream from existing palm oil mill infrastructure, verified and paid for through an automated monitoring system, could change that private calculus. We present Eagor-Core, a conceptual agentic artificial intelligence (AI) framework built on the Energy–AI Governance Orchestration (EAGOR) architecture. Eagor-Core converts palm oil mill effluent (POME) lagoons into microalgae cultivation units and links their output to zero-burn payments verified through a three-tier monitoring pipeline of in-ground sensors, autonomous drones, and satellite Earth observation. At the physical layer, we formalize multi-pond control as a decentralized partially observable Markov decision process (Dec-POMDP) with explicit sensor-drift and fouling states, and propose multi-agent reinforcement learning (MARL) under centralized training with decentralized execution. A bounded, volume-weighted health index (the Finamatrix vGRE) modulates a normalized multi-objective reward. At the governance layer, adaptive conformal inference provides prediction intervals whose width determines whether the system acts autonomously, falls back to a conservative policy, or enters a safe state and requests a signed human-in-the-loop (HITL) decision. We derive the minimum conditional payment that makes zero-burn compliance privately rational, and extend it to independent smallholders, who manage about 40% of Indonesia’s oil palm area, through a mill-level cooperative with conditional dividends. We also provide an assumption-based techno-economic scoping estimate for a 10-hectare estate, an evaluation protocol, and a three-stage research and rollout agenda. We report no simulation results, field validation, or multi-seed experiments; the techno-economic values are assumption-based scoping estimates intended to guide future work.

Keywords: agentic AI; Energy–AI Governance Orchestration (EAGOR); microalgae; palm oil mill effluent; Dec-POMDP; multi-agent reinforcement learning

JEL Codes: Q13; Q16; Q42; Q53; Q56; O33; C61; C63

1 Introduction

1.1 *The transboundary haze problem*

Seasonal transboundary haze across Southeast Asia is a recurring socio-economic and ecological crisis linked to fire-assisted land clearing and drainage on tropical peatlands in Sumatra and Kalimantan (Koh et al., 2011; Tacconi, 2016). Fire carbon emissions over maritime Southeast Asia in 2015 were the largest since 1997 (Huijnen et al., 2016), and exposure to the resulting fine particulate matter (PM_{2.5}) has been associated with substantial excess mortality across Indonesia, Malaysia, and Singapore (Marlier et al., 2013; Koplitz et al., 2016). The World Bank estimated the economic cost of Indonesia's 2015 fire season at about USD 16 billion (Glauber et al., 2016).

The legal framework is not absent. Indonesia's Law No. 32 of 2009 on Environmental Protection and Management (Republic of Indonesia, 2009) prohibits land clearing by burning, and the ASEAN Agreement on Transboundary Haze Pollution (ASEAN, 2002) commits member states to prevention, monitoring, and joint response. Enforcement is nonetheless hampered by the geographic extent of remote plantations, institutional lag, contested land tenure, and patronage relationships (Varkkey, 2013; Tacconi, 2016). Most importantly, fire remains cheaper than mechanical land preparation. In the language of the economics of crime (Becker, 1968), burning is privately rational whenever its cost advantage exceeds the expected penalty, and in remote estates, both the detection probability and the realized penalty are low. Information gaps compound the problem: the production and sharing of fire and haze data have been contested among states, which has weakened multilateral governance of the haze as an environmental health risk (Berti Suman, 2022).

1.2 *A circular alternative based on POME*

Palm oil mill effluent (POME) is a high-volume, organic-rich wastewater produced during crude palm oil (CPO) extraction; roughly 2.5–3.5 t of POME is generated per tonne of CPO (Bagchi et al., 2021; Low et al., 2021). Untreated POME has very high biochemical and chemical oxygen demand and is a major source of methane when held in open anaerobic lagoons (Wu et al., 2010; Lam & Lee, 2011). After appropriate pre-treatment and dilution, however, POME can serve as a nutrient source for microalgae such as *Chlorella* and *Scenedesmus*, which remove nitrogen, phosphorus, and organic load while producing lipid-rich biomass (Cheah et al., 2018; Hariz et al., 2019). Boiler flue gas can supply inorganic carbon to the cultures. The resulting crude algae oil (CAO) can be refined into a lipid feedstock for hydroprocessed esters and fatty acids (HEFA) jet fuel, and the defatted residue can be sold as protein meal.

Area-based productivity comparisons between microalgae and oil palm are highly sensitive to assumptions. Early optimistic estimates placed algal oil yields roughly an order of magnitude above oil palm (Chisti, 2007), whereas techno-economic and resource assessments of outdoor open ponds report considerably lower productivities and highlight cost, harvesting, and nutrient-supply constraints (Davis et al., 2011; Chisti, 2013; Quinn & Davis, 2015). We therefore use productivity figures derived from our own simulation and treat literature yields as bounds rather than targets.

1.3 Benchmarking existing haze-mitigation strategies

Table 1 compares the governance mechanisms and principal failure modes of four existing approaches with the mechanism proposed here. Legal prohibition fails mainly because detection is costly in remote peatlands while fire remains considerably cheaper than mechanical clearing (Tacconi, 2016). Voluntary certification under the Roundtable on Sustainable Palm Oil (RSPO) reduced deforestation on certified plantations but had no detectable effect on fire on peat (Carlson et al., 2018), and its audit costs are difficult for independent smallholders to bear (Jelsma et al., 2017). Crop switching imposes years of forgone income before new crops yield, and greenfield algae farms carry high capital costs and biological fragility (Chisti, 2013; Quinn & Davis, 2015).

Table 1. Benchmark of haze-mitigation strategies

Strategy	Governance mechanism	Primary failure mode	Eagor-Core response
Legal bans and fines (Law No. 32/2009)	Prosecution, land seizure, and administrative fines	Enforcement lag; remote peatlands make detection costly; fire remains cheaper than mechanical clearing	Raises detection probability through satellite MRV and adds a revenue stream that is forfeited if burning is detected
RSPO / ESG certification	Voluntary certification and supply-chain audits	Leakage of non-certified CPO to other markets; audit costs exclude smallholders; limited effect on fire	Mill-level aggregation lets smallholders participate without individual certification
Alternative crop switching	Conversion of peatland to non-palm crops	High transition cost and several years before the first harvest	Retrofits existing mill lagoons; first harvests within weeks of inoculation
Greenfield algae farms	Closed photobioreactors or new open ponds	High CAPEX, culture crashes, probe fouling, SO ₂ corrosion, high energy use	Lagoon retrofit with fault-tolerant MARL control and conformal deferral

Note. RSPO = Roundtable on Sustainable Palm Oil; ESG = environmental, social, and governance; MRV = measurement, reporting, and verification. The Eagor-Core column states design intentions; its performance is evaluated only in simulation in this paper.

1.4 The control and governance gap

Large-scale microalgae cultivation in open raceway ponds (ORPs) is fragile. Cultures are exposed to weather volatility, seasonal irradiance changes, grazing ciliates, viral and bacterial contamination, invasion by wild strains, and pH or dissolved-oxygen (DO) excursions (Day et al., 2012; Wang et al., 2013). Physical infrastructure adds a second layer of risk: optical and electrochemical probes foul and drift, paddlewheels fail, flue-gas lines corrode in the presence of sulfur dioxide (SO₂) and acidic condensate, and remote sites lose grid power and connectivity. Static rulebooks and single-loop proportional–integral–derivative (PID) controllers handle setpoint regulation well but are not designed for coupled, multi-objective decisions across many interconnected ponds under large and shifting uncertainty.

Reinforcement learning (RL) has been applied successfully to bioprocess control problems such as batch optimization, co-culture regulation, and fed-batch cyanobacterial production (Petsagkourakis et al., 2020; Treloar et al., 2020; Ma et al., 2020). These studies, however, treat a single reactor, assume reliable sensing, and do not connect process control to environmental verification or payment. Conversely, the literature on payments for ecosystem services (PES) and carbon market design emphasizes that payments only change behavior when they are conditional, additional, and reliably

verified (Engel et al., 2008; Jack et al., 2008; Schneider et al., 2015). No existing framework, to our knowledge, couples a fault-tolerant multi-pond controller with satellite-based zero-burn verification and an explicit rule for when automated decisions should be deferred to humans.

1.5 Contributions

This paper makes six contributions, all conceptual or methodological:

1. **Conceptual architecture and conversion manual.** We describe Eagor-Core, an agentic AI framework grounded in the EAGOR governance architecture (Chan & Wong, 2026a), with offline edge execution, automated sensor recalibration, and multi-tier fault recovery, together with a conversion manual for existing POME lagoons; the code is to be released under an open-source license (see Declarations).
2. **Dec-POMDP formulation with explicit sensor and fouling states.** We formulate multi-pond control as a Dec-POMDP whose state includes stochastic probe drift and a fouling process that is reset by backwashing. The observation function fuses three telemetry tiers: in-ground sensors, autonomous drones, and satellites.
3. **A bounded vGRE-modulated reward.** We redefine the Finamatrix Volume-Weighted Golden Ratio Estimator (vGRE) as a rolling, bounded health-weighted productivity index, and use golden-ratio weights as a convex default for the biomass–energy trade-off, subject to sensitivity analysis.
4. **Calibrated deferral under distribution shift.** We replace a static split-conformal rule with adaptive conformal inference over normalized residual scores, and give a precedence-ordered execution rule that is well defined when connectivity is lost.
5. **Incentive model, smallholder cooperative, and prospective techno-economic scoping.** We derive the minimum conditional payment that makes zero-burn compliance privately rational, extend it to a mill-level smallholder cooperative with conditional dividends, and give an assumption-based CAPEX/OPEX and break-even scoping estimate for a 10-hectare estate.
6. **Evaluation protocol and research agenda.** We specify the multi-seed protocol, stronger baselines, ablations, scalability tests, fault-escalation confusion matrix, field pilot, and life-cycle assessment needed before any performance or economic claim can be made.

The remainder of the paper is organized as follows. Section 2 reviews related work. Section 3 presents the incentive model. Section 4 describes the framework and its formalization. Section 5 specifies the proposed evaluation protocol and the hypotheses it is designed to test. Section 6 gives a prospective techno-economic scoping estimate under assumed yields. Section 7 discusses implications, a possible extension to vertical photobioreactors, limitations, and the research agenda, and Section 8 concludes. The appendices contain the field conversion manual, the smallholder cooperative model, the rollout plan, the simulator equations, and a policy brief.

2 Related Work

2.1 Haze, peatland fire, and economic incentives

Remote sensing has documented the large-scale conversion of peat swamp forest to oil palm (Koh et al., 2011), and atmospheric modeling has linked fire activity, El Niño conditions, and population exposure (Marlier et al., 2013; Koplitz et al., 2016). Policy analyses converge on the view that prohibition alone has not been effective. Tacconi (2016) argues that prevention requires changing the economic incentives for using fire, and Varkkey (2013) shows how patronage networks weaken enforcement. Economic theory offers two complementary levers: raising the expected penalty through better detection (Becker, 1968) and rewarding compliance through conditional payments (Engel et al., 2008; Jack et al., 2008). Egor-Core targets both by improving the probability and speed of detection and by tying a revenue stream to verified non-burning.

2.2 Microalgae cultivation on POME

POME treatment has traditionally relied on ponding systems, with growing interest in biogas capture and resource recovery (Wu et al., 2010; Lam & Lee, 2011; Tan et al., 2009). Laboratory and pilot studies show that microalgae can grow on diluted POME while removing nutrients and accumulating lipids (Cheah et al., 2018), and that indigenous strains can combine wastewater treatment with CO₂ fixation (Hariz et al., 2019). Reviews of algal biofuel production identify harvesting, dewatering, and contamination as the main barriers to commercial viability (Brennan & Owende, 2010; Chisti, 2013), and techno-economic assessments show that results are highly sensitive to areal productivity and lipid content (Davis et al., 2011; Quinn & Davis, 2015). Growth models for outdoor cultures typically combine light, temperature, and nutrient limitation terms (Béchet et al., 2013), and these models form the basis of the simulator specified here. Recent reviews confirm that large-scale microalgae cultivation on POME and other wastewaters is technically feasible, while identifying dilution, pre-treatment, and contamination control as the main obstacles to scale (Bagchi et al., 2021; Low et al., 2021).

2.3 Reinforcement learning for bioprocess control

Deep RL achieved human-level control in complex sequential tasks (Mnih et al., 2015), and its application to bioprocesses has grown rapidly. Petsagkourakis et al. (2020) used policy gradients for batch bioprocess optimization under plant–model mismatch, Treloar et al. (2020) regulated microbial co-cultures in chemostats, and Ma et al. (2020) combined neural network simulators with deep RL for fed-batch cyanobacterial production. Most recently, Gil et al. (2026) trained multi-agent DDPG controllers offline on historical expert-system data to regulate pH and dissolved oxygen jointly, and validated them in an industrial-scale open photobioreactor. Decentralized control of multiple coupled units is formally a Dec-POMDP, which is computationally hard to solve exactly (Bernstein et al., 2002; Oliehoek & Amato, 2016). Practical MARL methods therefore adopt centralized training with decentralized execution (CTDE), using a centralized critic during training and independent actors at run time (Lowe et al., 2017; Rashid et al., 2018; Yu et al., 2022; Zhang et al., 2021). Multi-objective rewards require care: scalarization weights embody value judgments (Rojers et al., 2013), and reward shaping can alter the optimal policy unless it is potential-based (Ng et al., 1999). Safe RL

methods add explicit constraints or fallback controllers when exploration or model error could cause damage (García & Fernández, 2015).

2.4 Uncertainty quantification and human oversight

Conformal prediction produces prediction sets with finite-sample, distribution-free coverage guarantees under exchangeability (Vovk et al., 2022; Lei et al., 2018; Angelopoulos & Bates, 2023). Standard split conformal intervals built on absolute residuals have constant width, which makes them unsuitable as an input-dependent uncertainty signal; locally weighted residuals (Lei et al., 2018) and conformalized quantile regression (Romano et al., 2019) restore adaptivity. Because sensor drift, seasonal change, and contamination violate exchangeability, methods that remain valid under shift are needed. Adaptive conformal inference (ACI) updates the miscoverage level online and guarantees long-run coverage under arbitrary shift (Gibbs & Candès, 2021), and weighted conformal methods bound the coverage gap under non-exchangeability (Barber et al., 2023). Human-in-the-loop machine learning provides the organizational counterpart: humans are consulted where model confidence is low, or stakes are high (Mosqueira-Rey et al., 2023).

2.5 Agentic AI governance and the EAGOR framework

Agentic AI systems increasingly act on physical infrastructure, which raises the question of how attention, escalation, and authority should be divided between machines and people. The EAGOR (Energy–AI Governance Orchestration) framework addresses the recursive dependence between energy infrastructure and the AI systems that control it by structuring attention, escalation, option activation, and adaptive redesign across autonomous agents and human stakeholders (Chan & Wong, 2026a). Related work proposes a framework and benchmark suite for human–AI collaborative decision-making under uncertainty (Chan et al., 2026) and multi-attribute decision frameworks for autonomous agents in bio-industrial bioprocessing (Chan & Pan, 2026). The vGRE used in this paper originated as a volume-weighted, golden-ratio-based overlay for drawdown and tail-risk control in financial portfolios (Chan & Wong, 2016, 2026b); Section 4.3 adapts it to a bounded physical health index. Because these frameworks are recent and partly unpublished, we use them as design principles and evaluate the resulting system on its own terms.

2.6 Verification, double counting, and data governance

Satellite products provide the observational basis for zero-burn verification. The MODIS Collection 6 active fire product (Giglio et al., 2016) and the VIIRS 375 m product (Schroeder et al., 2014) detect active fires, while Sentinel-1 C-band synthetic aperture radar (SAR) observes land-surface change through cloud and smoke (Torres et al., 2012). Credits derived from such verification face the risk of double-counting across registries and jurisdictions (Schneider et al., 2015); blockchain-based registries have been proposed to make issuance and transfer auditable (Franke et al., 2020). Cross-border data flows are governed in Singapore by the Personal Data Protection Act 2012 (Republic of Singapore, 2012) and in Indonesia by Law No. 27 of 2022 on Personal Data Protection (Republic of Indonesia, 2022), whose transition period ended in October 2024. Edge computing allows sensitive data to be processed close to where it is generated, reducing latency and exposure (Shi et al., 2016).

2.7 Smallholders and land-use decisions

Independent smallholders manage about 40% of Indonesia's oil palm area and are a heterogeneous group, ranging from local farmers with a few hectares to absentee investors (Jelsma et al., 2017; Euler et al., 2016). Smallholder expansion is driven by the high returns to oil palm relative to alternative crops (Euler et al., 2016), and smallholders typically lack the capital, legal documentation, and organizational capacity needed for certification (Jelsma et al., 2017). Because they sell fresh fruit bunches (FFB) to mills rather than processing them, the mill is the natural point at which a new revenue stream can be shared with them. Group-based conditional payments can harness social monitoring within communities, but they also raise free-rider and fairness concerns when one member's action affects everyone's payment (Engel et al., 2008).

2.8 Research gap

The literature contains strong components but no integrated system. Bioprocess RL studies stop at the reactor boundary; PES and carbon market studies assume verification without addressing the reliability of the underlying production system; and conformal prediction has rarely been used to govern when an industrial controller should hand control to humans. Eagor-Core addresses this gap by linking the three, and the incentive model in Section 3 makes explicit the economic condition under which the linkage changes land-use behavior.

3 Incentive Model for Zero-Burn Compliance

Consider an estate deciding whether to clear or prepare a parcel by fire (B) or mechanically (NB). Let c_F and c_M denote the per-hectare costs of fire-assisted and mechanical preparation, p the probability that burning is detected and sanctioned, F the expected fine, s a conditional zero-burn payment received only if verification confirms no burning, and ΔR the net operating margin from algae production, which is likewise forfeited if the estate is found to burn. Burning is privately preferred when

$$c_M - c_F > pF + s + \Delta R. \quad (1)$$

The minimum conditional payment that makes non-burning weakly preferred is therefore

$$s^* = \max\{0, (c_M - c_F) - pF - \Delta R\}. \quad (2)$$

Equation (2) has three implications. First, a higher detection probability p , which satellite verification provides, lowers the payment needed for compliance. Second, any positive net margin ΔR from the algae operation substitutes for public payment, which is the economic rationale for coupling the bioprocess to verification. Third, if $\Delta R \geq c_M - c_F$, compliance is self-enforcing and no external payment is required. Conditionality and additionality, the central design principles of PES schemes (Engel et al., 2008; Jack et al., 2008), are enforced through the rolling 30-day verification window described in Section 4.6.

Extension to smallholder cooperatives. Smallholders do not own mills and cannot capture ΔR directly. Under the proposed mill-cooperative structure, the mill operates the algae facility on its lagoon footprint and distributes a share θ of its net algae and credit revenue NR to the smallholders

who supply it, in proportion to FFB deliveries and conditional on zero-burn verification of their registered village geofence v . The dividend to smallholder j in village v in a settlement period is

$$d_j = \theta \cdot NR \cdot \frac{FFB_j}{\sum_k FFB_k} \cdot g(\beta_v), \quad g(\beta_v) = \max\left\{0, 1 - \frac{\beta_v}{\bar{\beta}}\right\}. \quad (3)$$

Substituting the expected dividend for ΔR in Equation (1), a smallholder refrains from burning when $c_M - c_F \leq pF + \mathbb{E}[d_j]$. Because the condition applies at village level, each smallholder's dividend also depends on neighbours' behaviour, which creates an incentive for mutual monitoring. The same feature exposes compliant farmers to losses caused by others, so Equation (3) uses a graduated rule: β_v is the share of the geofence area with verified burning in the period, confirmed by HITL review, and $\bar{\beta} > 0$ is the burned share at which the village dividend falls to zero. The binary rule 1{no verified fire in geofence v } is the limiting case $\bar{\beta} \rightarrow 0$.

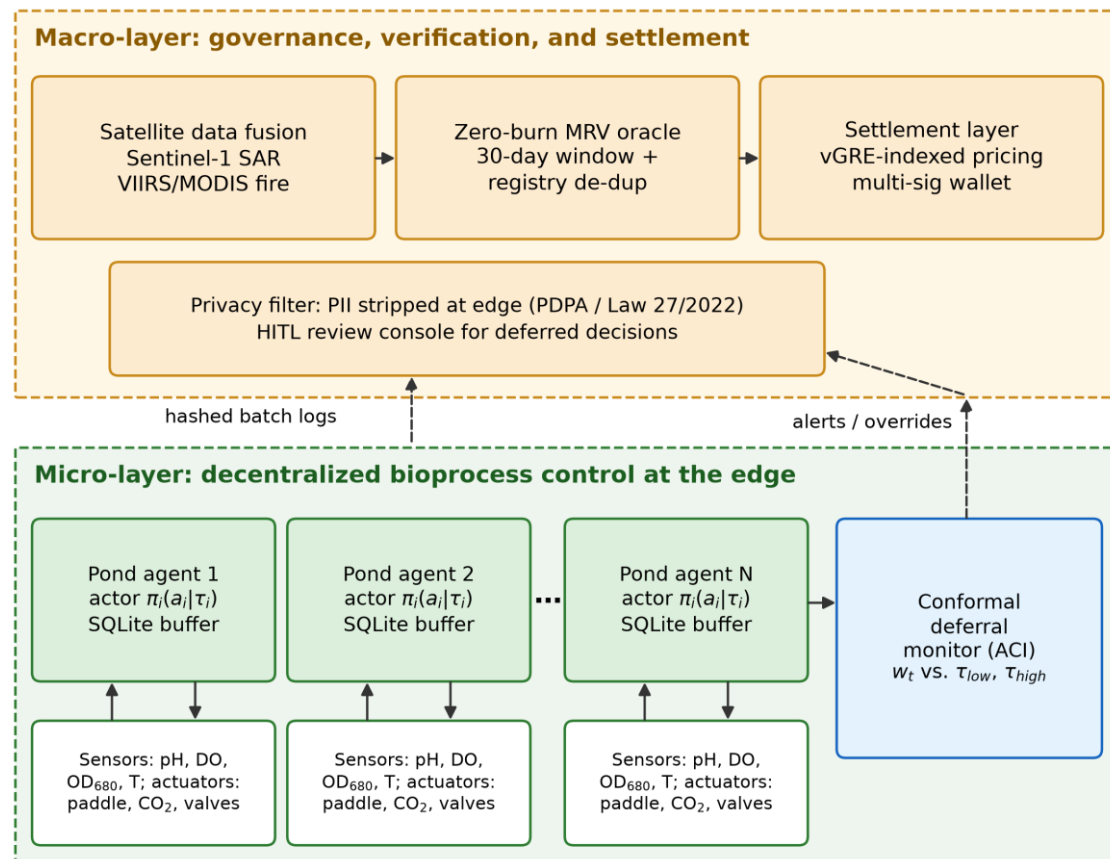
Free-riding, fairness, and review. A village-level condition is a collective incentive. Each member bears only part of the loss caused by a fire but captures the full private benefit of burning, so free-riding becomes more likely as villages grow, while compliant members are penalized for fires they did not set. Two refinements reduce both problems. First, when a drone inspection attributes a verified fire to a registered plot, the reduction is applied to that member's dividend, and $g(\beta_v)$ applies only to the burned area that cannot be attributed. Second, every flag passes a review procedure with fixed time limits: the cooperative is notified within 7 days of a satellite flag, a drone inspection and HITL decision follow within 14 days, and affected members may appeal to a mill-cooperative committee within 30 days, before the dividend is settled. A formal game-theoretic analysis of the resulting monitoring equilibrium is left to future work.

4 Eagor-Core Framework

4.1 Dual-layer topology

Eagor-Core operates on two layers (Figure 1). The **micro-layer** consists of distributed edge controllers, one per pond or pond cluster, that run decentralized policies, keep a local state buffer, and govern paddlewheel speed, CO₂ injection, scrubber bypass valves, effluent dilution and harvesting pumps, as well as automated backwashing and sensor recalibration. The **macro-layer** fuses satellite observations to verify zero-burn compliance across estate boundaries, de-duplicates credit claims across registries, applies privacy filters to all outbound data, hosts the HITL review console, and settles payments.

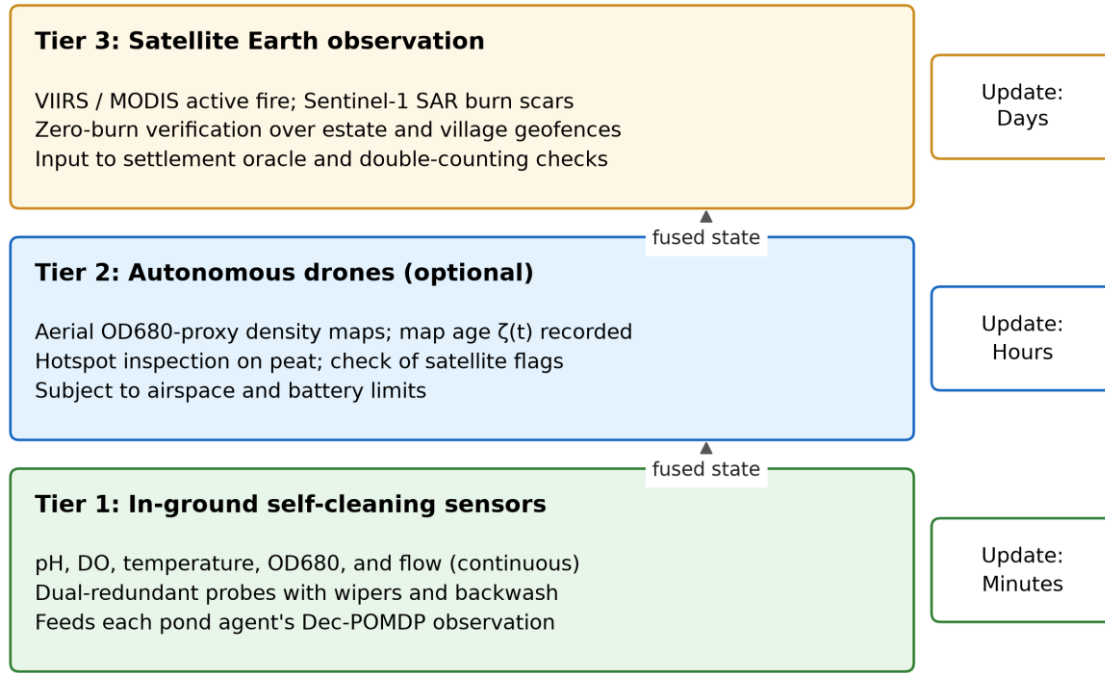
Figure 1. Dual-layer architecture of Eagor-Core



Note. Solid arrows show the main data flow within each layer; dashed arrows show cross-layer messages. Decentralized actors execute locally and do not require connectivity; the centralized critic is used only during training. PII = personally identifiable information; ACI = adaptive conformal inference; MRV = measurement, reporting, and verification.

Both layers draw on a three-tier telemetry pipeline (Figure 2). Tier 1 consists of in-ground, self-cleaning sensor arrays (pH, DO, temperature, OD₆₈₀, and flow) that sample continuously and form the core of each agent's observation. Tier 2 consists of autonomous drones with multispectral cameras and LiDAR, operated from a docking station on the mill site; they map biomass density across the pond grid at intervals of hours, inspect suspected hotspots on adjacent peatland, and check satellite fire flags before any payment is withheld. Tier 3 consists of satellite Earth observation, namely VIIRS and MODIS active-fire products and Sentinel-1 SAR change detection, which verify zero-burn status over estate and village geofences at intervals of days. Each higher tier covers a larger area at a lower frequency, so the tiers complement rather than replace one another. Drone flights must comply with national rules on unmanned aircraft, which limit altitude, range, and operation beyond visual line of sight. Flights over smallholder land are covered by the FPIC agreement with each village, and imagery outside the pond grid is used only for fire inspection and is not retained after review.

Figure 2. Three-tier telemetry pipeline of Eagor-Core



Note. Update intervals are indicative. Tier 1 data form the observation of each pond agent (Equation 5); Tier 2 maps enter that observation as the drone-derived feature $z_i(t)$ when available; Tier 3 data are used by the macro-layer for zero-burn verification and settlement. OD₆₈₀ = optical density at 680 nm; LiDAR = light detection and ranging; SAR = synthetic aperture radar. Tier 2 is optional: flights depend on airspace rules and battery availability, and the age of the latest map, $\zeta_i(t)$, is passed to the agents with it.

4.2 Dec-POMDP formulation

We model an estate with N raceway ponds as a Dec-POMDP (Bernstein et al., 2002; Oliehoek & Amato, 2016) defined by the tuple

$$\mathcal{M} = \langle \mathcal{N}, \mathcal{S}, \{\mathcal{A}_i\}_{i \in \mathcal{N}}, P, R, \{\Omega_i\}_{i \in \mathcal{N}}, O, \gamma \rangle, \quad (4)$$

where $\mathcal{N} = \{1, \dots, N\}$ is the set of pond agents, $\mathcal{S}$ the global state space (culture, water chemistry, equipment and weather states), $\mathcal{A}_i$ the action space of agent i , P the transition kernel, R the shared team reward, Ω_i the local observation space, O the observation function and $\gamma \in [0, 1]$ the discount factor. The global state is partitioned as $s_t = (x_t^{\text{bio}}, x_t^{\text{chem}}, x_t^{\text{hw}}, x_t^{\text{env}})$: culture states (biomass density and pond volume), water chemistry (pH, DO, dissolved inorganic carbon, nitrogen, phosphorus, and toxicity), hardware states (probe drift δ , optical fouling ϕ , and equipment health), and exogenous weather and grid states. Because drift and fouling evolve over time and are reset by actions, they belong to the state and their dynamics, Equations (6) and (7), are part of the transition kernel P ; the observation function O maps these states to what each agent sees. The discount factor lies in $[0, 1]$ so that the infinite-horizon objective is finite; with a finite evaluation horizon T , $\gamma = 1$ is also admissible.

Observation model. The local observation of agent i is

$$\tilde{o}_i(t) = [\text{pH}_i + \delta_i^{\text{pH}}, \text{DO}_i + \delta_i^{\text{DO}}, \text{OD}_{680,i}(1 - \phi_i), T_i, Q_i, I(t), \chi(t), z_i(t), \zeta_i(t)]^T + \varepsilon_i(t), \quad (5)$$

where Q_i is the inflow rate, $I(t)$ the photosynthetically active irradiance, $\chi(t)$ an index of POME toxicity (phenolics and heavy metals), and $\varepsilon_i(t) \sim \mathcal{N}(0, \Sigma_\varepsilon)$ white measurement noise; $z_i(t)$ is a

drone-derived biomass-density feature for pond i , taken from the most recent multispectral map and held at its last value between flights, and $\zeta_i(t)$ is the age of that map, which lets agents discount stale data; time indices on the pond states are omitted for readability. Probe drift follows a bounded random walk that is reset by calibration, and optical fouling is a bounded, monotone process that is reset by a backwash action:

$$\delta_i^k(t+1) = (1 - c_i(t)) \Pi_{[-\bar{\delta}_k, \bar{\delta}_k]}(\delta_i^k(t) + \xi_i^k(t)), \quad \xi_i^k(t) \sim \mathcal{N}(0, \sigma_k^2), \quad k \in \{\text{pH}, \text{DO}\}, \quad (6)$$

$$\phi_i(t+1) = (1 - b_i(t)) \min\{1, \phi_i(t) + \kappa_f\}, \quad (7)$$

where κ_f is the fouling increment per control interval and $b_i(t) \in \{0,1\}$ is the backwash trigger. Drift is detected by comparing the readings of the redundant probe pair, and a calibration routine is scheduled when their divergence exceeds a tolerance. In Equation (6), Π denotes projection onto $[-\bar{\delta}_k, \bar{\delta}_k]$, the largest drift the redundant-probe check tolerates before a reading is rejected, and $c_i(t) \in \{0, 1\}$ indicates a completed calibration, which resets drift to zero. The projection prevents the unbounded growth of a pure random walk, and the resulting drift process is stationary between calibrations.

Action space. Each agent selects

$$a_i(t) = [\omega_i, q_i^{\text{CO}_2}, q_i^{\text{POME}}, q_i^{\text{H}}, v_i, b_i, u_i]^\top, \quad (8)$$

where ω_i is the paddlewheel speed, $q_i^{\text{CO}_2}$, q_i^{POME} and q_i^{H} are the CO_2 -injection, effluent-feed, and harvest flow rates, $v_i \in [0,1]$ is the scrubber bypass valve position and $b_i(t) \in \{0,1\}$ the backwash trigger, and $u_i(t) \in \{0, 1\}$ requests a drone survey of pond i . Survey requests are queued and served subject to battery and airspace constraints, and each flight adds to the energy term E_t . Continuous actions are bounded by actuator limits, and a hard-coded safety layer clips any action that would violate pH, DO or hydraulic constraints before it reaches the actuators.

Hybrid action space. The action vector mixes continuous components (ω_i , the three flow rates, and v_i) with binary triggers (b_i and u_i). Each actor therefore has a Gaussian head for the continuous components, squashed to actuator bounds, and independent Bernoulli heads for the binary triggers, so that the policy factorizes as $\pi_{\theta_i}(a_i | \tau_i) = \pi_{\theta_i}^c(a_i^c | \tau_i) \pi_{\theta_i}^b(a_i^b | \tau_i)$. This parameterization is compatible with policy-gradient CTDE methods such as MAPPO (Yu et al., 2022), whose likelihood ratios are computed from the product of the two heads.

4.3 The Finamatrix vGRE index

The vGRE summarizes how productively a pond has converted effluent into biomass on healthy equipment. Three properties are required for its use inside a reward: it must respond to recent deterioration rather than average over the entire history, it must not double-count current biomass, and it must be dimensionless so that it can scale other reward terms. We therefore define vGRE as a dimensionless rolling index:

$$G_t = \frac{\sum_{k=t-W+1}^t V_k H_k \left(\frac{B_k}{B_{\max}} \right)}{\sum_{k=t-W+1}^t V_k}, \quad G_t \in [0,1], \quad (9)$$

where V_k is the POME volume processed in interval k , $H_k \in [0,1]$ is a composite hardware-health index (Section 5.3), B_k is biomass density, $B_{\max}$ is the design carrying capacity and W is the window length. Because each weight $V_k/\sum V_k$ is non-negative and sums to one, and $H_k B_k/B_{\max} \in [0,1]$, G_t is a convex combination and is therefore bounded in $[0, 1]$. A high G_t indicates that the pond has recently processed substantial effluent while maintaining dense cultures on healthy equipment.

4.4 Reward design

The reward balances biomass gain, energy use, culture-crash risk, and corrosion exposure. Golden-ratio constants are used as weights in a form that has a clear meaning: since $\phi^{-1} + \phi^{-2} = 1$, the pair $w_B = \phi^{-1} \approx 0.618$ and $w_E = \phi^{-2} \approx 0.382$ defines a convex weighting of biomass gain against energy use. All terms are normalized by reference values so that they are dimensionless:

$$r_t = \left(\frac{1}{2} + \frac{1}{2} G_t \right) \left[w_B \frac{\Delta B_t}{\Delta B_{\text{ref}}} - w_E \frac{E_t}{E_{\text{ref}}} \right] - \kappa \max\{0, \hat{p}_t - \bar{p}\} - \lambda \frac{S_t}{S_{\text{ref}}}. \quad (10)$$

Here ΔB_t is the estate-level biomass gain, E_t the electrical energy used, $\hat{p}_t$ the predicted probability of a culture crash within the forecast horizon (from a calibrated classifier trained on simulated trajectories), $\bar{p}$ a tolerated crash probability, S_t the SO_2 exposure of the gas-handling equipment, and $\kappa, \lambda > 0$ penalty weights. The factor $1/2 + 1/2 G_t \in [0.5,1]$ scales the productive component by recent operating quality without suppressing the learning signal entirely when G_t is low. The hinge term replaces the discontinuous indicator with a continuous penalty that grows with the excess risk. The weights $(w_B, w_E, \kappa, \lambda)$ are value judgments (Roijers et al., 2013); the golden-ratio pair is a transparent default, not an optimality result, and Section 5.4 specifies the sensitivity analysis over these weights.

The team objective is to find decentralized policies $\pi = (\pi_1, \dots, \pi_N)$ that maximize

$$J(\pi) = \mathbb{E}_{\pi} \left[\sum_{t=0}^T \gamma^t r_t \right]. \quad (11)$$

Policies are trained under CTDE: each actor $\pi_{\theta_i}(a_i | \tau_i)$ conditions only on its local action–observation history τ_i , while a centralized critic uses the global state during training (Lowe et al., 2017; Yu et al., 2022). This structure is what allows the actors to keep running when the estate network is unavailable.

4.5 Adaptive conformal deferral

Design requirements. Split conformal prediction provides a marginal *coverage* guarantee, $\Pr\{Y_{t+h} \in \hat{C}_{\alpha}(X_t)\} \geq 1 - \alpha$, under exchangeability (Lei et al., 2018). Two features of the deferral problem require modifications. First, with the usual absolute-residual score the interval width is

identical for every input, so a threshold on width cannot separate easy states from hard ones. Second, sensor drift, seasonality and contamination events violate exchangeability.

Revised procedure. Let $\hat{\mu}(X_t)$ be a forecaster of a target Y_{t+h} (here, biomass density $h = 24$ hours ahead, normalized by $B_{\max}$), and $\hat{\sigma}(X_t) > 0$ a model of its conditional spread, both fitted on a training split. On a calibration split of size n we compute normalized residual scores, in which each absolute residual is scaled by the estimated conditional spread (Lei et al., 2018):

$$R_j = \frac{|Y_j - \hat{\mu}(X_j)|}{\hat{\sigma}(X_j)}, \quad j = 1, \dots, n, \quad (12)$$

and form the interval

$$\hat{C}_{\alpha_t}(X_t) = [\hat{\mu}(X_t) \pm \hat{q}_{\alpha_t} \hat{\sigma}(X_t)], \quad \hat{q}_{\alpha_t} = \text{the } [(n+1)(1-\alpha_t)]\text{-th smallest of } \{R_j\}, \quad (13)$$

whose width $w_t = 2 \hat{q}_{\alpha_t} \hat{\sigma}(X_t)$ now varies with the input. To maintain calibration under shift, the working miscoverage level is updated online by adaptive conformal inference (Gibbs & Candès, 2021): If $[(n+1)(1-\alpha_t)] > n$, the quantile is set to infinity and the interval is unbounded. Calibration points receive equal weight, so this is not a weighted conformal procedure: adaptivity to the input comes only through $\hat{\sigma}$, and robustness to distribution shift comes from the online update below. Weighting calibration points by their similarity to X_t (Barber et al., 2023) is a possible extension.

$$\alpha_{t+1} = \Pi_{[0,1]}(\alpha_t + \eta(\alpha - \text{err}_t)), \quad \text{err}_t = \mathbf{1}\{Y_t \notin \hat{C}_{\alpha_{t-h}}(X_{t-h})\}, \quad (14)$$

where α is the target miscoverage (0.1 in our experiments) and $\eta > 0$ is a step size, and $\Pi_{[0,1]}$ projects the working level onto $[0, 1]$; when α_t reaches 0, the interval is unbounded and the safe state is entered. When intervals miss too often, α_t falls, and intervals widen; when they over-cover, intervals tighten. ACI guarantees that the long-run miscoverage rate converges to α without distributional assumptions. Because conformal intervals capture total predictive uncertainty, we refer to w_t as a predictive uncertainty signal rather than a measure of epistemic uncertainty alone.

Execution rule. Because network loss can coincide with very high uncertainty, and a HITL request cannot be delivered without a network, the execution rule (Figure 3) evaluates conditions in a fixed order of precedence, so that exactly one mode applies at each step, with $\tau_{\text{low}} < \tau_{\text{high}}$:

$$m_t = \begin{cases} \text{Safe state + signed HITL request,} & w_t \geq \tau_{\text{high}} \text{ and network available} \\ \text{Safe state + buffered alert,} & w_t \geq \tau_{\text{high}} \text{ and network unavailable} \\ \text{Conservative fallback policy } \pi^{\text{fb}}, & \tau_{\text{low}} < w_t < \tau_{\text{high}} \\ \text{Autonomous MARL policy } \pi_{\theta}, & w_t \leq \tau_{\text{low}} \end{cases}. \quad (15)$$

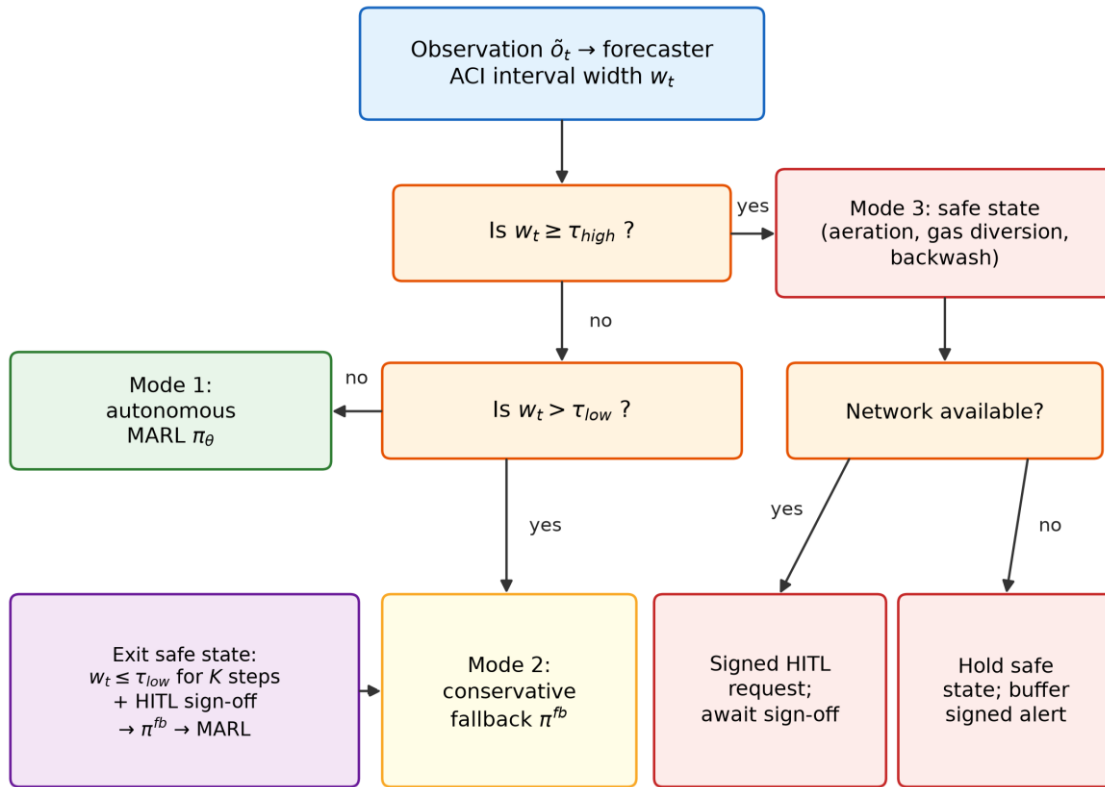
The safe state applies maximum aeration, diverts flue gas, requests a drone survey for aerial confirmation, and triggers backwashing. Signed requests are queued in the local buffer and transmitted when connectivity returns, so that every override is auditable. Because decentralized actors run locally, network loss alone does not force a change of mode; it only removes the HITL

channel. Thresholds τ_{low} and τ_{high} are set on held-out data as the 70th and 95th percentiles of w_t under normal operation.

Cost-sensitive thresholds. The percentiles above are initial values only. In the full evaluation, τ_{low} and τ_{high} are chosen on a validation set to minimize the expected cost $c_{\text{FN}}n_{\text{FN}} + c_{\text{FP}}n_{\text{FP}} + c_{\text{H}}n_{\text{H}}$, where n_{FN} counts crash episodes that were not deferred, n_{FP} counts deferrals not followed by a crash within the forecast horizon, n_{H} counts HITL requests, and $c_{\text{FN}} > c_{\text{FP}} > c_{\text{H}}$ reflect the relative costs of a culture crash, an unnecessary safe state, and operator time. The resulting confusion matrix is reported with the chosen thresholds.

Exit from the safe state. The system leaves the safe state when $w_t \leq \tau_{\text{low}}$ for K consecutive intervals and, if a HITL request was issued, the signed response has been received. It then passes through the conservative fallback policy before the MARL policy resumes, which prevents oscillation between modes. If the network remains unavailable, the safe state is held for at most T_{safe} ; after that, the edge controller switches to the fallback policy, keeps the alert buffered, and repeats the backwash and calibration routine.

Figure 3. Precedence-ordered execution logic under adaptive conformal deferral



Note. w_t is the width of the adaptive conformal interval for the 24-hour-ahead biomass forecast. The high-uncertainty test is evaluated first, so the safe state is always entered when $w_t \geq \tau_{\text{high}}$, regardless of connectivity. HITL = human-in-the-loop. The system leaves the safe state only after the exit condition of Section 4.5 is met, passing through the fallback policy before MARL control resumes.

4.6 Macro-layer verification and settlement

Zero-burn status is evaluated over a rolling 30-day window for each registered estate polygon. An estate is flagged if any VIIRS 375 m or MODIS active-fire detection with nominal or high confidence falls within the polygon or a buffer around it, or if Sentinel-1 backscatter change

indicates a new burn scar. Flags trigger a drone inspection of the flagged location and HITL review rather than an automatic penalty, which limits the cost of false positives from, for example, flaring at the mill. Each harvested batch is hashed together with the estate identifier, period, and verification status, and the hash is checked against registry records before a credit is issued, which prevents the same batch from being claimed twice (Schneider et al., 2015; Franke et al., 2020). Outbound telemetry is stripped of personally identifiable information at the edge; operational data remains in Indonesia while financial settlement is executed in Singapore, consistent with the cross-border transfer provisions of both jurisdictions' data protection laws.

5 Proposed Evaluation Protocol

5.1 Simulation environment

The proposed evaluation uses a physical–biological simulator of ten open raceway ponds of 500 m³ each (operating depth 25 cm and surface area 2,000 m², about 2 ha in total), fed with pre-treated POME under Southeast Asian climatic conditions. Specific growth rate follows the multiplicative structure common in outdoor productivity models (Béchet et al., 2013):

$$\mu_i(t) = \mu_{\max} f_I(I(t)) f_T(T_i(t)) f_{\text{pH}}(\text{pH}_i(t)) (1 - \chi(t)), \quad (16)$$

$$\frac{dB_i}{dt} = (\mu_i(t) - m - D_i(t)) B_i(t) - \frac{q_i^{\text{POME}}(t) + q_i^{\text{rain}}(t) - q_i^{\text{evap}}(t)}{V_i(t)} B_i(t), \quad (17)$$

where f_I , f_T and $f_{\text{pH}} \in [0,1]$ are limitation functions for light, temperature, and pH; m is the maintenance (respiration) rate; $D_i(t)$ a stochastic loss rate representing grazing and contamination, and V_i the pond volume. Disturbances comprise diurnal temperatures of 24–38 °C, monsoonal cloud cover, irradiance spikes, fluctuations in heavy-metal and phenolic load, pH, and DO probe drift according to Equation (6), fouling according to Equation (7), and random 4-hour grid outages.

Equation (17) follows from mass balances for biomass and water. Harvesting removes culture at the pond concentration and therefore lowers the biomass stock without changing B_i , whereas inflows of POME and rain dilute the culture and evaporation concentrates it; the pond volume follows the water balance in Table A2, and an overflow weir keeps V_i within design limits. The water-chemistry states that enter the observation and the reward (pH, DO, dissolved inorganic carbon, nitrogen, phosphorus, and the toxicity index χ) follow the balance equations summarized in Table A2.

5.2 Baselines

The proposed evaluation compares Egor-Core with three simple controllers: (i) a static rule-based schedule; (ii) independent single-loop PID controllers for pH, DO, and paddlewheel speed, tuned per pond; and (iii) a single-agent deep Q-network (DQN; Mnih et al., 2015) controlling all ponds with a discretized joint action space. Because these baselines are deliberately simple, the evaluation also includes three stronger comparators: MAPPO with independent actors and a centralized critic (Yu et al., 2022), QMIX value decomposition (Rashid et al., 2018), and a nonlinear model predictive controller that uses the simulator equations over a 24-hour horizon. The single-agent DQN mainly

illustrates the cost of a centralized controller, because its discretized joint action space grows exponentially with the number of ponds.

5.3 Performance metrics

To make the results reproducible, every metric is defined explicitly.

Biomass stability index (BSI). One minus the coefficient of variation of daily estate-level biomass productivity P_d over the evaluation horizon, truncated at zero and expressed as a percentage:

$$\text{BSI} = 100 \times \max \left\{ 0, 1 - \frac{\text{sd}(P_d)}{\text{mean}(P_d)} \right\}. \quad (18)$$

Mean time between culture crashes (MTBCC). Total pond-days divided by the number of crash events, where a crash is a fall in biomass density of more than 50% within 48 hours.

Net biomass yield. Harvested dry biomass per hectare per year, net of biomass used for re-inoculation.

Fault recovery rate. The share of injected fault episodes (sensor drift, fouling, actuator failure, contamination, outage) after which the pond returned to within 10% of its pre-fault productivity within 72 hours without manual intervention. Episodes that triggered a HITL request are counted as not recovered autonomously.

Hardware-health index H_t . The mean of normalized health scores for probes (inverse of drift magnitude), paddlewheel drive (inverse of torque anomaly) and gas lines (inverse of cumulative SO_2 exposure), each scaled to $[0, 1]$.

5.4 Protocol and statistical analysis (planned)

None of the following has yet been executed; it is the protocol proposed for future work. Each controller will be evaluated over at least ten independent random seeds and disturbance realizations, and results are reported as means with standard deviations and 95% bootstrap confidence intervals, because point estimates from a few RL runs are known to be unreliable (Henderson et al., 2018; Agarwal et al., 2021). Pairwise differences between Egor-Core and each baseline are tested with the Mann–Whitney U test with Holm correction for multiple comparisons. The ablation study removes, one at a time, (a) the vGRE modulation, (b) conformal deferral, (c) the backwash and drift-detection actions, and (d) multi-agent decomposition. Sensitivity analysis varies w_B over $[0.5, 0.8]$ (with $w_E = 1 - w_B$) and κ, λ over an order of magnitude. Conformal calibration is reported as empirical coverage against the 90% target, overall and within each disturbance regime. Two further ablations address the telemetry tiers: (e) removal of drone inputs, with z_i and ζ_i masked, and (f) delayed or corrupted drone maps. Scalability is tested by repeating the evaluation with 25 and 50 ponds, the latter matching the 10-hectare estate of Section 6. Fault-recovery results are reported as a confusion matrix of escalation decisions against crash outcomes.

Hypotheses. The protocol is designed to test three hypotheses about why the architecture might outperform the baselines; none is supported by evidence in this paper. H1: Decentralized actors

respond to local disturbances, such as fouling in one pond, more effectively than a single centralized controller. H2: including drift detection and backwashing in the action space lets the controller maintain its own sensors rather than act on corrupted readings. H3: Conformal deferral prevents the learned policy from acting in states far from its training distribution, which should appear as fewer crashes among episodes that were not escalated. Ablations (d), (c), and (b), respectively, isolate each mechanism, and the fault-escalation confusion matrix tests H3 directly.

6 Prospective Techno-Economic Scoping

6.1 Capital and operating costs

This section gives a prospective scoping estimate based on engineering cost assumptions and assumed yields; it is not an investment case, and no value in it comes from simulation or field data. Table 2 itemizes the CAPEX of converting a 10-hectare lagoon system, and Table 3 the annual OPEX. The ten line items sum to USD 382,000; with a 15% contingency of USD 57,300, total CAPEX is USD 439,300. Annual OPEX totals USD 93,000, including USD 8,000 for drone maintenance, battery replacement, and software subscriptions. Lining is the largest single item (Figure 4).

Table 2. Capital expenditure for a 10-hectare estate conversion

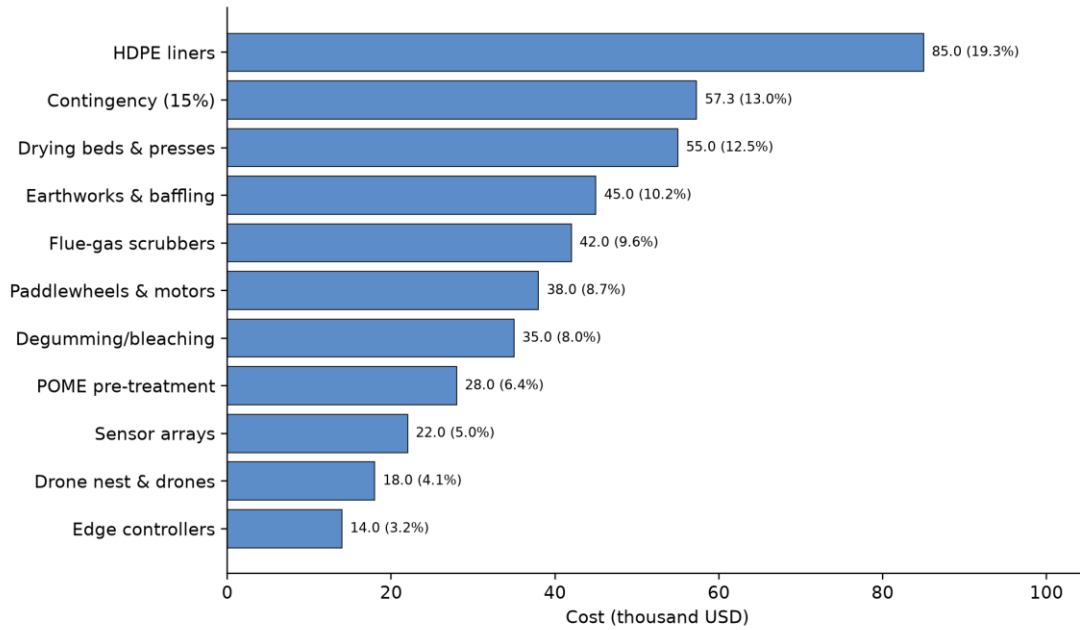
Item	Cost (USD)	Share (%)
Lagoon earthworks, grading and baffling	45,000	10.2
HDPE liners (1.5 mm, UV-stabilized, 10 ha)	85,000	19.3
Paddlewheels and redundant biogas/solar gear motors	38,000	8.7
Alkaline packed-tower flue-gas scrubbers and 316L headers	42,000	9.6
POME pre-treatment and alum metal-settling units	28,000	6.4
Self-cleaning dual sensor arrays and wiper assemblies	22,000	5.0
Drone docking station, charging pad, and two drones (multispectral and LiDAR)	18,000	4.1
Redundant edge controllers (single-board computer + microcontroller)	14,000	3.2
Solar drying beds and mechanical lipid-extraction presses	55,000	12.5
Degumming and bleaching pre-refining unit	35,000	8.0
Contingency (15% of the above)	57,300	13.0
Total CAPEX	439,300	100.0

Note. Costs are engineering estimates in 2025–2026 US dollars for a retrofit of existing POME lagoons; land is not included. Shares may not sum exactly to 100 due to rounding.

Table 3. Annual operating expenditure for a 10-hectare operation

Item	Annual cost (USD)
Electrical backup and biogas power maintenance	12,000
Probe replacement, reagents, and scrubber alkali	15,000
Drone maintenance, battery replacement, and software subscriptions	8,000
Satellite connectivity and software maintenance	6,000
Local agronomist and technician labor	24,000
Community FPIC and smallholder profit-sharing reserve	18,000
Re-inoculation and contamination contingency	10,000
Total annual OPEX	93,000

Note. FPIC = free, prior, and informed consent. Cooperative dividends under Equation (3) are paid from net revenue and are not part of OPEX; the reserve covers administration and minimum community payments. Feedstock costs are excluded because POME and flue gas are mill by-products; this assumes the mill does not already sell them.

Figure 4. Composition of capital expenditure for the 10-hectare conversion

Note. Data from Table 2. Values are in thousand USD, with each item's share of total CAPEX (USD 439,300) in parentheses.

6.2 Annualized cost and break-even revenue

CAPEX is annualized with the capital recovery factor

$$\text{CRF}(r, n) = \frac{r(1 + r)^n}{(1 + r)^n - 1}, \quad (19)$$

and the break-even revenue per tonne of dry biomass is

$$p^{\text{BE}} = \frac{\text{CAPEX} \cdot \text{CRF}(r, n) + \text{OPEX}}{Y \cdot A}, \quad (20)$$

where Y is the net biomass yield and $A = 10$ ha. Because no field or validated simulation yield is available, Y is treated as a scenario parameter with three values: 25, 35, and 45 t ha⁻¹ yr⁻¹, corresponding to annual average areal productivities of about 6.8, 9.6, and 12.3 g m⁻² d⁻¹. All three lie below the 25 g m⁻² d⁻¹ open-pond base case assumed by Davis et al. (2011), because long-term outdoor productivity is typically lower and more variable than such targets (Quinn & Davis, 2015). The analysis also assumes that productivity per hectare does not depend on the number of ponds; the 10-hectare estate corresponds to about 50 ponds of the size specified in Section 5.1, which the 50-pond scalability runs of Section 5.4 and Stage 2 of the rollout are designed to test. With an economic life of $n = 10$ years, Table 4 reports the break-even revenue at three discount rates and the three yield scenarios.

Table 4. Annualized cost and break-even biomass revenue (scoping estimate)

Discount rate r	CRF	Annualized CAPEX (USD yr ⁻¹)	Total annual cost (USD yr ⁻¹)	Break-even revenue at $Y = 25 / 35 / 45$ (USD t ⁻¹ biomass)
8%	0.1490	65,469	158,469	634 / 453 / 352
10%	0.1627	71,494	164,494	658 / 470 / 366
12%	0.1770	77,749	170,749	683 / 488 / 379

Note. Y = assumed net biomass yield in $\text{t ha}^{-1} \text{yr}^{-1}$; these are scenario values, not measured or simulated yields. Assumes a 10-year life and zero salvage value. Taxes, insurance, and cost inflation are not included.

The break-even revenue is compared with oil and meal revenue only; zero-burn payments are treated as a separate transfer whose minimum size is given by Equation (2). At a lipid content of 20–30% of dry weight, the three yield scenarios correspond to roughly 5.0–13.5 t of crude algae oil per hectare per year.

6.3 Revenue scenarios

Revenue per tonne of dry biomass is $R = \ell p_{\text{CAO}} + (1 - \ell) p_{\text{meal}}$, where ℓ is the extractable lipid share and p_{CAO} and p_{meal} are the prices of crude algae oil and defatted meal. Neither product has an established market price at scale, so Table 5 benchmarks them against crude palm oil and soybean meal, whose 2023–2025 annual average prices ranged from USD 886 to $1,007 \text{ t}^{-1}$ and from USD 366 to 541 t^{-1} , respectively, and stood at USD 1,180 and 447 t^{-1} in September 2026 (World Bank, 2026). The low scenario prices CAO at half the 2023 palm oil price and meal at 60% of the 2025 soybean meal price, reflecting quality discounts for unproven products; the central scenario prices CAO at 80% of the 2025 palm oil price and meal at par with 2025 soybean meal; the high scenario uses September 2026 prices at par. Results are pre-tax, exclude zero-burn payments, and use $r = 10\%$.

Table 5. Revenue scenarios and annual net margin for the 10-hectare estate (scoping estimate)

Scenario	Lipid share ℓ	CAO price (USD t^{-1})	Meal price (USD t^{-1})	Revenue (USD t^{-1} biomass)	Net margin at $Y = 25 / 35 / 45$ (USD yr^{-1})
Low	0.20	443	220	265	−98,344 / −71,884 / −45,424
Central	0.25	806	366	476	−45,494 / 2,106 / 49,706
High	0.30	1,180	447	667	2,231 / 68,921 / 135,611

Note. Net margin = $R \times Y \times 10 \text{ ha}$ – total annual cost at $r = 10\%$ (USD 164,494; Table 4), for assumed yields Y of 25, 35, and $45 \text{ t ha}^{-1} \text{yr}^{-1}$. Prices are benchmarks derived from the World Bank (2026), not forecasts. CAO = crude algae oil.

Under these assumptions, the estate would break even at central prices only if the yield reaches about $35 \text{ t ha}^{-1} \text{yr}^{-1}$, and at $25 \text{ t ha}^{-1} \text{yr}^{-1}$, only the high price scenario would cover costs. The economic case, therefore, depends as much on field productivity as on prices, which is why Stage 1 measures yield before the Stage 2 investment.

7 Discussion and Research Agenda

7.1 Policy implications

The incentive model in Section 3 shows that the economic case for the system rests on two parameters that policy can influence: the detection probability p and the net margin ΔR . Satellite-based verification raises p at very low marginal cost, and a profitable algae operation raises ΔR without a fiscal transfer. Where ΔR alone does not cover the cost advantage of fire, Equation (2) gives the minimum conditional payment, which can be financed by voluntary carbon buyers, SAF off-takers seeking traceable feedstock, or public programs. Because payments are conditional on a rolling verification window and reviewed by humans before penalties are applied, the design follows established principles for PES schemes (Engel et al., 2008; Jack et al., 2008).

The cooperative extension matters because independent smallholders manage a large share of the planted area but are poorly served by certification (Jelsma et al., 2017; Carlson et al., 2018). Routing algae revenue through the mill gives them a stake in non-burning without requiring them to invest or certify individually. The village-level condition in Equation (3) creates peer monitoring, and the graduated, plot-attributable rule in Section 3 limits the losses that compliant farmers suffer from others' fires.

7.2 Future extension: vertical photobioreactors and firm low-carbon power

Open raceways remain exposed to contamination, weather, and land constraints. A longer-term extension of the framework would replace or supplement lagoon raceways with automated vertical photobioreactor (PBR) towers. One such concept, the AMTS-IoT Vertical Class proposed by EVES Energy, stacks modular glass and stainless-steel PBR units vertically and couples them to an IoT sensing layer and automated culture regulation with continuous partial harvesting and culture return. Each unit maps directly onto an agent of the Dec-POMDP in Section 4.2, so the control and deferral layers of Eager-Core would apply without structural change. A further concept, Project AAI-Green Nexus, would pair such towers with a small modular reactor (SMR) supplying continuous low-carbon electricity for pumping, lighting, and control, and waste heat for biomass drying, harvesting, and lipid extraction. Its intended outputs are algae oil as a sustainable aviation fuel feedstock, protein-rich biomass, and biologically captured CO₂.

Neither concept has been built or tested, and both raise questions this paper does not address. Closed PBRs have historically had much higher production costs than open ponds; in the base case of Davis et al. (2011), the cost of lipid production was USD 18.10 per gallon for tubular PBRs against USD 8.52 for open ponds. Artificial lighting adds a large energy penalty. SMR deployment would require licensing, siting and safety assessment, and public acceptance in Singapore and Indonesia, neither of which currently operates a nuclear power plant. We therefore treat the vertical PBR–SMR pathway as a research direction for the framework's control and governance layers. It is not part of the techno-economic scoping in Section 6, which is limited to lagoon retrofits.

7.3 Limitations and threats to validity

This study has several limitations. First, the paper reports no performance results: neither the simulator nor the controllers have yet been evaluated, and the yields in Section 6 are assumptions; field productivity of outdoor ponds is typically lower and more variable than modeled, and contamination dynamics are particularly hard to simulate (Day et al., 2012; Wang et al., 2013). Second, the hypotheses H1–H3 remain untested, so whether each component contributes anything is unknown. Third, the claim that the system is “carbon-negative” cannot be supported without a life-cycle assessment: carbon fixed in algae oil is released when the fuel is combusted, so the net balance depends on displaced fossil fuel, avoided methane from POME lagoons, and avoided peat fires, none of which are quantified here. We therefore describe the system as low-carbon pending such an assessment. Fourth, CAO is a feedstock, not a fuel: it must be hydroprocessed in a HEFA facility, and the finished blend must meet ASTM D7566 (ASTM International, 2026). The impurity limits cited in the appendix are illustrative of off-taker requirements, not certified specifications. Fifth, the architecture relies on MODIS products for continuity, but the MODIS instruments are near the end of their missions; VIIRS should be treated as the primary active-fire source. Sixth, the cooperative

dividend has not been calibrated to actual FFB volumes and prices, and tokenized membership units may raise regulatory questions. Seventh, the drone tier adds cost and raises airspace and privacy issues: flights over smallholder plots require community consent, imagery must be limited to the pond grid and fire inspection, and its contribution to control performance has not yet been isolated (ablations (e) and (f) in Section 5.4). Finally, the open-source claim can be verified only once the repository described under Declarations is public.

Research agenda. The claims of this paper become testable in four steps: (i) the multi-seed protocol of Section 5.4, with MAPPO, QMIX, and nonlinear MPC baselines, ablations (a)–(f), the fault-escalation confusion matrix, and the 25- and 50-pond scalability runs; (ii) a Stage 1 pilot on an operating mill to replace the assumed yields with measured field productivity; (iii) a life-cycle assessment to test carbon claims; and (iv) a cooperative field study to calibrate FFB volumes, dividend shares, and HITL review times.

8 Conclusion

Eagor-Core is a conceptual framework that links three things usually studied separately: fault-tolerant control of microalgae ponds, calibrated rules for deferring decisions to humans, and conditional payments for verified non-burning. Its contributions are a Dec-POMDP formulation with sensor-drift, fouling, and water-chemistry states; a bounded vGRE-modulated reward; adaptive conformal deferral with a precedence-ordered execution rule and safe-state exit conditions; an incentive model with a graduated smallholder dividend; and an evaluation protocol. The evaluation protocol and the techno-economic scoping estimate show how the framework would be assessed, not whether it works or pays. The research agenda in Section 7 sets out the multi-seed evaluation, field pilot, and life-cycle assessment needed to test it.

Declarations

Conflict of interest. Lanz CWJ Chan is affiliated with Finamatrix Quant-Lab, which developed the vGRE indicator and the Eagor-Core software. The policy brief in Appendix B requests public co-funding for a demonstration facility in which Finamatrix Quant-Lab may participate. Shin-Hung Pan declares no competing interests. The vertical photobioreactor and SMR concepts discussed in Section 7.2 (AMTS-IoT Vertical Class and Project AAI-Green Nexus) are proposed by EVES Energy and Finamatrix, with which Lanz CWJ Chan is associated.

Data and code availability. No datasets were generated or analyzed in this conceptual study. The simulator specification is given in Section 5.1 and Table A2; code implementing the framework and the evaluation protocol will be deposited in a public repository with a persistent identifier before any results are reported.

References

- ASEAN. (2002). *ASEAN Agreement on Transboundary Haze Pollution*. ASEAN Secretariat.
- ASTM International. (2026). *Standard specification for aviation turbine fuel containing synthesized hydrocarbons* (ASTM D7566-26a). ASTM International.
- Agarwal, R., Schwarzer, M., Castro, P. S., Courville, A. C., & Bellemare, M. G. (2021). Deep reinforcement learning at the edge of the statistical precipice. *Advances in Neural Information Processing Systems*, 34, 29304–29320.
- Angelopoulos, A. N., & Bates, S. (2023). Conformal prediction: A gentle introduction. *Foundations and Trends in Machine Learning*, 16(4), 494–591. <https://doi.org/10.1561/22000000101>
- Bagchi, S. K., Patnaik, R., & Prasad, R. (2021). Feasibility of utilizing wastewaters for large-scale microalgal cultivation and biofuel productions using hydrothermal liquefaction technique: A comprehensive review. *Frontiers in Bioengineering and Biotechnology*, 9, Article 651138. <https://doi.org/10.3389/fbioe.2021.651138>
- Barber, R. F., Candès, E. J., Ramdas, A., & Tibshirani, R. J. (2023). Conformal prediction beyond exchangeability. *The Annals of Statistics*, 51(2), 816–845. <https://doi.org/10.1214/23-AOS2276>
- Béchet, Q., Shilton, A., & Guieysse, B. (2013). Modeling the effects of light and temperature on algae growth: State of the art and critical assessment for productivity prediction during outdoor cultivation. *Biotechnology Advances*, 31(8), 1648–1663. <https://doi.org/10.1016/j.biotechadv.2013.08.014>
- Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of Political Economy*, 76(2), 169–217. <https://doi.org/10.1086/259394>
- Bernstein, D. S., Givan, R., Immerman, N., & Zilberstein, S. (2002). The complexity of decentralized control of Markov decision processes. *Mathematics of Operations Research*, 27(4), 819–840. <https://doi.org/10.1287/moor.27.4.819.297>
- Berti Suman, A. (2022). The role of information in multilateral governance of environmental health risk: Lessons from the Equatorial Asian haze case. *Journal of Risk Research*, 25(8), 959–975. <https://doi.org/10.1080/13669877.2019.1617338>
- Brennan, L., & Owende, P. (2010). Biofuels from microalgae—A review of technologies for production, processing, and extractions of biofuels and co-products. *Renewable and Sustainable Energy Reviews*, 14(2), 557–577. <https://doi.org/10.1016/j.rser.2009.10.009>
- Carlson, K. M., Heilmayr, R., Gibbs, H. K., Noojipady, P., Burns, D. N., Morton, D. C., Walker, N. F., Paoli, G. D., & Kremen, C. (2018). Effect of oil palm sustainability certification on deforestation and fire in Indonesia. *Proceedings of the National Academy of Sciences*, 115(1), 121–126. <https://doi.org/10.1073/pnas.1704728114>
- Chan, L. C. W., & Pan, S.-H. V. (2026). *Multi-attribute decision frameworks for autonomous agent operations in bio-industrial bioprocessing* [Working paper]. Finamatrix Quant-Lab.
- Chan, L. C. W., & Wong, W.-K. (2016). *vGRE-Lite: Volume-weighted golden ratio estimator for safe-haven regime detection* [Working paper]. Finamatrix Quant-Lab.
- Chan, L. C. W., & Wong, W.-K. (2026a). *EAGOR: Energy-AI governance orchestration in recursive decision architectures* [Working paper]. Finamatrix Quant-Lab.
- Chan, L. C. W., & Wong, W.-K. (2026b). Volume-weighted golden ratio estimator (vGRE) for drawdown and tail-risk control for wealth portfolios. *International Journal of Wealth*

- Management, 2, 1–23. <https://ijwm.scibiz.world/volume-weighted-golden-ratio-estimator-vgre-for-drawdown-and-tail-risk-control-for-wealth-portfolios>
- Chan, L. C. W., Pan, S.-H. V., & Wong, W.-K. (2026). *Human–AI collaborative decision-making under uncertainty: The HACDU framework and benchmark suite* [Working paper]. Finamatrix Quant-Lab.
- Cheah, W. Y., Show, P. L., Juan, J. C., Chang, J.-S., & Ling, T. C. (2018). Microalgae cultivation in palm oil mill effluent (POME) for lipid production and pollutants removal. *Energy Conversion and Management*, 174, 430–438. <https://doi.org/10.1016/j.enconman.2018.08.057>
- Chisti, Y. (2007). Biodiesel from microalgae. *Biotechnology Advances*, 25(3), 294–306. <https://doi.org/10.1016/j.biotechadv.2007.02.001>
- Chisti, Y. (2013). Constraints to commercialization of algal fuels. *Journal of Biotechnology*, 167(3), 201–214. <https://doi.org/10.1016/j.jbiotec.2013.07.020>
- Civil Aviation Authority of Singapore. (2024). *Singapore sustainable air hub blueprint*. <https://www.caas.gov.sg/sustainability/sustainable-air-hub-blueprint>
- Civil Aviation Authority of Singapore. (2026, September 3). *CAAS to start sustainable aviation fuel levy for origin-destination passengers, general and business aviation flights from 1 October 2026 for flights departing from 1 January 2027* [Press release]. <https://www.caas.gov.sg/resources/media-and-publication/newsroom/caas-to-start-sustainable-aviation-fuel-levy-for-origin-destination-passengers-from-1-october-2026-for-flights-departing-from-1-january-2027>
- Davis, R., Aden, A., & Pienkos, P. T. (2011). Techno-economic analysis of autotrophic microalgae for fuel production. *Applied Energy*, 88(10), 3524–3531. <https://doi.org/10.1016/j.apenergy.2011.04.018>
- Day, J. G., Slocombe, S. P., & Stanley, M. S. (2012). Overcoming biological constraints to enable the exploitation of microalgae for biofuels. *Bioresource Technology*, 109, 245–251. <https://doi.org/10.1016/j.biortech.2011.05.033>
- Doliente, S. S., Narayan, A., Tapia, J. F. D., Samsatli, N. J., Zhao, Y., & Samsatli, S. (2020). Bio-aviation fuel: A comprehensive review and analysis of the supply chain components. *Frontiers in Energy Research*, 8, Article 110. <https://doi.org/10.3389/fenrg.2020.00110>
- Engel, S., Pagiola, S., & Wunder, S. (2008). Designing payments for environmental services in theory and practice: An overview of the issues. *Ecological Economics*, 65(4), 663–674. <https://doi.org/10.1016/j.ecolecon.2008.03.011>
- Euler, M., Schwarze, S., Siregar, H., & Qaim, M. (2016). Oil palm expansion among smallholder farmers in Sumatra, Indonesia. *Journal of Agricultural Economics*, 67(3), 658–676. <https://doi.org/10.1111/1477-9552.12163>
- Franke, L., Schletz, M., & Salomo, S. (2020). Designing a blockchain model for the Paris Agreement's carbon market mechanism. *Sustainability*, 12(3), 1068. <https://doi.org/10.3390/su12031068>
- García, J., & Fernández, F. (2015). A comprehensive survey on safe reinforcement learning. *Journal of Machine Learning Research*, 16(42), 1437–1480.
- Gibbs, I., & Candès, E. (2021). Adaptive conformal inference under distribution shift. *Advances in Neural Information Processing Systems*, 34, 1660–1672.

- Giglio, L., Schroeder, W., & Justice, C. O. (2016). The collection 6 MODIS active fire detection algorithm and fire products. *Remote Sensing of Environment*, 178, 31–41. <https://doi.org/10.1016/j.rse.2016.02.054>
- Gil, J. D., Del Rio Chanona, E. A., Guzmán, J. L., & Berenguel, M. (2026). *From learning to control: Data-driven multi-agent reinforcement learning for multivariable control in a microalgae bioprocess* (arXiv:2609.09313). arXiv. <https://doi.org/10.48550/arXiv.2609.09313>
- Glauber, A. J., Moyer, S., Adriani, M., & Gunawan, I. (2016). *The cost of fire: An economic analysis of Indonesia's 2015 fire crisis* (Indonesia Sustainable Landscapes Knowledge Note No. 1). World Bank.
- Hariz, H. B., Takriff, M. S., Mohd Yasin, N. H., Ba-Abbad, M. M., & Mohd Hakimi, N. I. N. (2019). Potential of the microalgae-based integrated wastewater treatment and CO₂ fixation system to treat palm oil mill effluent (POME) by indigenous microalgae; *Scenedesmus* sp. and *Chlorella* sp. *Journal of Water Process Engineering*, 32, 100907. <https://doi.org/10.1016/j.jwpe.2019.100907>
- Henderson, P., Islam, R., Bachman, P., Pineau, J., Precup, D., & Meger, D. (2018). Deep reinforcement learning that matters. *Proceedings of the AAAI Conference on Artificial Intelligence*, 32(1). <https://doi.org/10.1609/aaai.v32i1.11694>
- Huijnen, V., Wooster, M. J., Kaiser, J. W., Gaveau, D. L. A., Flemming, J., Parrington, M., Inness, A., Murdiyarso, D., Main, B., & van Weele, M. (2016). Fire carbon emissions over maritime southeast Asia in 2015 largest since 1997. *Scientific Reports*, 6, 26886. <https://doi.org/10.1038/srep26886>
- Jack, B. K., Kousky, C., & Sims, K. R. E. (2008). Designing payments for ecosystem services: Lessons from previous experience with incentive-based mechanisms. *Proceedings of the National Academy of Sciences*, 105(28), 9465–9470. <https://doi.org/10.1073/pnas.0705503104>
- Jelsma, I., Schoneveld, G. C., Zoomers, A., & van Westen, A. C. M. (2017). Unpacking Indonesia's independent oil palm smallholders: An actor-disaggregated approach to identifying environmental and social performance challenges. *Land Use Policy*, 69, 281–297. <https://doi.org/10.1016/j.landusepol.2017.08.012>
- Koh, L. P., Miettinen, J., Liew, S. C., & Ghazoul, J. (2011). Remotely sensed evidence of tropical peatland conversion to oil palm. *Proceedings of the National Academy of Sciences*, 108(12), 5127–5132. <https://doi.org/10.1073/pnas.1018776108>
- Kopplitz, S. N., Mickley, L. J., Marlier, M. E., Buonocore, J. J., Kim, P. S., Liu, T., Sulprizio, M. P., DeFries, R. S., Jacob, D. J., Schwartz, J., Pongsiri, M., & Myers, S. S. (2016). Public health impacts of the severe haze in Equatorial Asia in September–October 2015: Demonstration of a new framework for informing fire management strategies to reduce downwind smoke exposure. *Environmental Research Letters*, 11(9), 094023. <https://doi.org/10.1088/1748-9326/11/9/094023>
- Lam, M. K., & Lee, K. T. (2011). Renewable and sustainable bioenergies production from palm oil mill effluent (POME): Win–win strategies toward better environmental protection. *Biotechnology Advances*, 29(1), 124–141. <https://doi.org/10.1016/j.biotechadv.2010.10.001>
- Lei, J., G'Sell, M., Rinaldo, A., Tibshirani, R. J., & Wasserman, L. (2018). Distribution-free predictive inference for regression. *Journal of the American Statistical Association*, 113(523), 1094–1111. <https://doi.org/10.1080/01621459.2017.1307116>

- Low, S. S., Bong, K. X., Mubashir, M., Cheng, C. K., Lam, M. K., Lim, J. W., Ho, Y. C., Lee, K. T., Munawaroh, H. S. H., & Show, P. L. (2021). Microalgae cultivation in palm oil mill effluent (POME) treatment and biofuel production. *Sustainability*, 13(6), Article 3247. <https://doi.org/10.3390/su13063247>
- Lowe, R., Wu, Y., Tamar, A., Harb, J., Abbeel, P., & Mordatch, I. (2017). Multi-agent actor-critic for mixed cooperative-competitive environments. *Advances in Neural Information Processing Systems*, 30, 6379–6390.
- Ma, Y., Noreña-Caro, D. A., Adams, A. J., Brentzel, T. B., Romagnoli, J. A., & Benton, M. G. (2020). Machine-learning-based simulation and fed-batch control of cyanobacterial-phyocyanin production in *Plectonema* by artificial neural network and deep reinforcement learning. *Computers & Chemical Engineering*, 142, 107016. <https://doi.org/10.1016/j.compchemeng.2020.107016>
- Marlier, M. E., DeFries, R. S., Voulgarakis, A., Kinney, P. L., Randerson, J. T., Shindell, D. T., Chen, Y., & Faluvegi, G. (2013). El Niño and health risks from landscape fire emissions in southeast Asia. *Nature Climate Change*, 3(2), 131–136. <https://doi.org/10.1038/nclimate1658>
- Ministry of Sustainability and the Environment. (2026, June 29). *Singapore and Indonesia sign Memorandum of Understanding on Environmental Cooperation* [Press release]. <https://www.mse.gov.sg/latest-news/singapore-and-indonesia-sign-memorandum-of-understanding-on-environmental-cooperation>
- Ministry of Trade and Industry. (2026, July 6). *Singapore and Indonesia sign Memorandum of Understanding on Carbon Credits Collaboration* [Press release]. <https://www.mti.gov.sg/newsroom/singapore-and-indonesia-sign-memorandum-of-understanding-on-carbon-credits-collaboration/>
- Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., Graves, A., Riedmiller, M., Fidjeland, A. K., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S., & Hassabis, D. (2015). Human-level control through deep reinforcement learning. *Nature*, 518(7540), 529–533. <https://doi.org/10.1038/nature14236>
- Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascarán, J., & Fernández-Leal, Á. (2023). Human-in-the-loop machine learning: A state of the art. *Artificial Intelligence Review*, 56(4), 3005–3054. <https://doi.org/10.1007/s10462-022-10246-w>
- Ng, A. Y., Harada, D., & Russell, S. (1999). Policy invariance under reward transformations: Theory and application to reward shaping. In *Proceedings of the Sixteenth International Conference on Machine Learning* (pp. 278–287). Morgan Kaufmann.
- Oliehoek, F. A., & Amato, C. (2016). *A concise introduction to decentralized POMDPs*. Springer. <https://doi.org/10.1007/978-3-319-28929-8>
- Petsagkourakis, P., Sandoval, I. O., Bradford, E., Zhang, D., & del Rio-Chanona, E. A. (2020). Reinforcement learning for batch bioprocess optimization. *Computers & Chemical Engineering*, 133, 106649. <https://doi.org/10.1016/j.compchemeng.2019.106649>
- Quinn, J. C., & Davis, R. (2015). The potentials and challenges of algae based biofuels: A review of the techno-economic, life cycle, and resource assessment modeling. *Bioresource Technology*, 184, 444–452. <https://doi.org/10.1016/j.biortech.2014.10.075>
- Rashid, T., Samvelyan, M., Schroeder de Witt, C., Farquhar, G., Foerster, J., & Whiteson, S. (2018). QMIX: Monotonic value function factorisation for deep multi-agent reinforcement learning.

In *Proceedings of the 35th International Conference on Machine Learning* (PMLR 80, pp. 4295–4304).

Republic of Indonesia. (2009). *Law No. 32 of 2009 on Environmental Protection and Management*.

Republic of Indonesia. (2022). *Law No. 27 of 2022 on Personal Data Protection*.

Republic of Singapore. (2012). *Personal Data Protection Act 2012* (Act No. 26 of 2012).

Roiijers, D. M., Vamplew, P., Whiteson, S., & Dazeley, R. (2013). A survey of multi-objective sequential decision-making. *Journal of Artificial Intelligence Research*, 48, 67–113. <https://doi.org/10.1613/jair.3987>

Romano, Y., Patterson, E., & Candès, E. (2019). Conformalized quantile regression. *Advances in Neural Information Processing Systems*, 32, 3543–3553.

Schneider, L., Kollmuss, A., & Lazarus, M. (2015). Addressing the risk of double counting emission reductions under the UNFCCC. *Climatic Change*, 131(4), 473–486. <https://doi.org/10.1007/s10584-015-1398-y>

Schroeder, W., Oliva, P., Giglio, L., & Csiszar, I. A. (2014). The New VIIRS 375 m active fire detection data product: Algorithm description and initial assessment. *Remote Sensing of Environment*, 143, 85–96. <https://doi.org/10.1016/j.rse.2013.12.008>

Shi, W., Cao, J., Zhang, Q., Li, Y., & Xu, L. (2016). Edge computing: Vision and challenges. *IEEE Internet of Things Journal*, 3(5), 637–646. <https://doi.org/10.1109/JIOT.2016.2579198>

Tacconi, L. (2016). Preventing fires and haze in Southeast Asia. *Nature Climate Change*, 6(7), 640–643. <https://doi.org/10.1038/nclimate3008>

Tan, K. T., Lee, K. T., Mohamed, A. R., & Bhatia, S. (2009). Palm oil: Addressing issues and towards sustainable development. *Renewable and Sustainable Energy Reviews*, 13(2), 420–427. <https://doi.org/10.1016/j.rser.2007.10.001>

Torres, R., Snoeij, P., Geudtner, D., Bibby, D., Davidson, M., Attema, E., Potin, P., Rommen, B., Floury, N., Brown, M., Navas Traver, I., Deghaye, P., Duesmann, B., Rosich, B., Miranda, N., Bruno, C., L'Abbate, M., Croci, R., Pietropaolo, A., . . . Rostan, F. (2012). GMES Sentinel-1 mission. *Remote Sensing of Environment*, 120, 9–24. <https://doi.org/10.1016/j.rse.2011.05.028>

Treloar, N. J., Fedorec, A. J. H., Ingalls, B., & Barnes, C. P. (2020). Deep reinforcement learning for the control of microbial co-cultures in bioreactors. *PLOS Computational Biology*, 16(4), e1007783. <https://doi.org/10.1371/journal.pcbi.1007783>

Varkkey, H. (2013). Patronage politics, plantation fires and transboundary haze. *Environmental Hazards*, 12(3–4), 200–217. <https://doi.org/10.1080/17477891.2012.759524>

Vovk, V., Gammernan, A., & Shafer, G. (2022). *Algorithmic learning in a random world* (2nd ed.). Springer. <https://doi.org/10.1007/978-3-031-06649-8>

Wang, H., Zhang, W., Chen, L., Wang, J., & Liu, T. (2013). The contamination and control of biological pollutants in mass cultivation of microalgae. *Bioresource Technology*, 128, 745–750. <https://doi.org/10.1016/j.biortech.2012.10.158>

World Bank. (2026). *World Bank commodities price data (The Pink Sheet), October 2026*. <https://thedocs.worldbank.org/en/doc/74e8be41ceb20fa0da750cda2f6b9e4e-0050012026/related/CMO-Pink-Sheet-October-2026.pdf>

Wu, T. Y., Mohammad, A. W., Jahim, J. M., & Anuar, N. (2010). Pollution control technologies for the treatment of palm oil mill effluent (POME) through end-of-pipe processes. *Journal of*

Environmental Management, 91(7), 1467–1490.
<https://doi.org/10.1016/j.jenvman.2010.02.008>

Yu, C., Velu, A., Vinitsky, E., Gao, J., Wang, Y., Bayen, A., & Wu, Y. (2022). The surprising effectiveness of PPO in cooperative multi-agent games. *Advances in Neural Information Processing Systems*, 35, 24611–24624.

Zhang, K., Yang, Z., & Başar, T. (2021). Multi-agent reinforcement learning: A selective overview of theories and algorithms. In K. G. Vamvoudakis, Y. Wan, F. L. Lewis, & D. Cansever (Eds.), *Handbook of reinforcement learning and control* (pp. 321–384). Springer.
https://doi.org/10.1007/978-3-030-60990-0_12

Appendix A. Low-CAPEX Palm Oil Estate Transformation Manual

A practical field guide for plantation owners, engineers, and cooperatives

A.1 Overview and financial rationale

This manual describes how to convert existing POME lagoons into microalgae cultivation units. Repurposing mill infrastructure (lagoons, boilers, biogas generators) avoids land acquisition and much of the civil work of a greenfield plant. A drone docking station and two drones are added to the standard retrofit to support Tier 2 monitoring.

Table A1. Comparison of a conventional CPO estate with an Eagor-Core transformed estate

Metric		Conventional CPO estate (fire-assisted expansion)	Eagor-Core transformed estate
Primary cost	feedstock	High (land acquisition, fertilizer)	Near zero (POME and boiler CO ₂ as by-products)
Additional required	land	New land for expansion	None (existing lagoon footprint)
Annual oil yield		About 3–4 t CPO ha ⁻¹ yr ⁻¹	About 5.0–13.5 t CAO ha ⁻¹ yr ⁻¹ (assumed yield scenarios; 20–30% lipid)
Environmental compliance		Exposure to sanctions under Law No. 32/2009	Reduced effluent discharge; carbon balance subject to LCA
Product		Standard CPO	CAO as HEFA feedstock (illustrative limit ≤ 15 ppm total metals and phosphorus)
Smallholder inclusion		Marginalized; pressure to expand by burning	Cooperative dividends from mill algae revenue, conditional on zero-burn verification
Settlement latency		Months (conventional supply chains)	Under 12 hours after verification (smart contract)

Note. CAO yield is derived from the assumed biomass yields of 25–45 t ha⁻¹ yr⁻¹ (Section 6) and an assumed lipid content of 20–30%; it is not a measured or simulated value. LCA = life-cycle assessment; HEFA = hydroprocessed esters and fatty acids.

A.2 Smallholder inclusion and cooperative business model

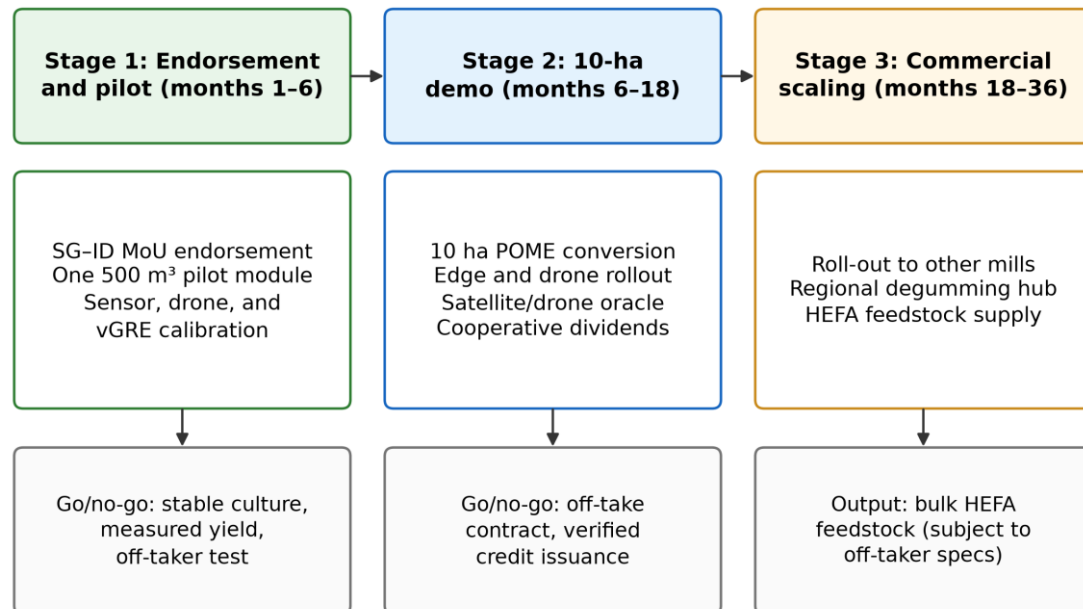
Independent smallholders manage about 40% of Indonesia's oil palm area (Jelsma et al., 2017). Because they have no mills of their own, certification-based policies often exclude them, and expansion by burning remains tempting. Eagor-Core therefore uses a mill-cooperative aggregation structure:

1. *Mill-level aggregation.* The palm oil mill (*pabrik kelapa sawit*, PKS) builds the raceway facility on its central POME lagoon footprint, so smallholders bear no land or capital cost.
2. *Cooperative membership.* Smallholders who supply FFB to the mill are registered as cooperative members and receive digital membership units recorded on the settlement ledger.
3. *Dividend mechanics.* A share θ of net revenue from CAO sales and verified credits is distributed quarterly in proportion to FFB deliveries, following Equation (3).
4. *Conditionality.* Dividends are reduced in proportion to the verified burned share of the village geofence (Equation 3), and fires that drones attribute to a registered plot reduce only that member's dividend. Each reduction follows HITL review and can be appealed before settlement.

If the membership units are transferable tokens, they may fall under securities or crypto-asset regulation in Indonesia; a non-transferable ledger entry avoids this question.

A.3 Three-stage commercial rollout

Figure 5. Three-stage commercial rollout roadmap



Note. Durations are planning targets. Each stage proceeds only if the go/no-go criteria shown at its end are met. HEFA = hydroprocessed esters and fatty acids.

1. *Stage 1: Bilateral endorsement and pilot (months 1–6).* Seek endorsement under existing bilateral instruments, such as the Singapore–Indonesia Memorandum of Understanding (MoU) on Environmental Cooperation (Ministry of Sustainability and the Environment, 2026) and the MoU on carbon credits collaboration under Article 6 of the Paris Agreement (Ministry of Trade and Industry, 2026). Retrofit a single 500 m³ lagoon module (about 0.2 ha). Validate culture stability, calibrate the edge controllers, drones, and vGRE parameters under local weather, test CAO quality against off-taker feedstock limits, and measure field productivity to replace the simulated yield in the payback assessment.
2. *Stage 2: 10-hectare demonstration (months 6–18).* Expand to the complete 10-hectare facility, deploy redundant edge controllers, wet scrubbers, and drones, integrate drone and satellite verification into the settlement oracle, sign an off-take agreement, and activate cooperative dividend settlement.
3. *Stage 3: Commercial scaling (months 18–36).* Use the demonstration results to attract private investment and extend the system to other mills, and establish a regional pre-refining hub that aggregates CAO from ten or more neighboring mills and performs centralized degumming and bleaching, supplying bulk HEFA feedstock to refiners whose jet fuel blends are certified under ASTM D7566.

A.4 Risk management framework

Biological and contamination risks.

- *Wild strains, viruses, and ciliates.* Apply periodic pulse-dosing of mild organic acids or salinity shocks scheduled by Eagor-Core. Maintain high-density inocula in closed photobioreactor (PBR) seed tanks to reseed ponds immediately after contamination (Wang et al., 2013).
- *Heavy metals and POME toxicity.* Pre-treat POME through anaerobic digestion traps, alum coagulation, and settling basins to remove heavy metals (Cr, Pb, Cd) and excess solids before the effluent enters the ponds (Wu et al., 2010).
- *Seasonal light and temperature variability.* Adjust culture depth dynamically, for example, toward 15 cm on overcast days to improve light availability and toward 30 cm during intense heat to buffer temperature and limit photoinhibition.

Hardware and infrastructure degradation.

- *Sensor fouling and probe drift.* Install dual-redundant pH and DO probes with mechanical wipers and pressurized backwash rings. Eagor-Core detects drift through cross-probe divergence (Equation 6).
- *Paddlewheel failures and power outages.* Pair low-wattage gear motors with dual-feed power switching to mill biogas generators and solar battery backup. Fit shear-pin protection on paddlewheel axles.
- *Flue-gas scrubber and pipe corrosion.* Route flue gas through an alkaline packed-tower scrubber to remove SO₂ and capture acidic condensate before it reaches the PVC headers and 316L stainless steel nozzles.
- *Loss of connectivity.* Edge controllers run fully autonomously on local SQLite state databases. When the satellite link fails, decentralized policies continue, and audit logs are buffered until connectivity resumes.
- *Drone failure and airspace restrictions.* Treat drone data as optional inputs: agents fall back on Tier 1 and Tier 3 data when flights are grounded by weather, battery faults, or airspace restrictions, and the age indicator in the observation flags stale maps.

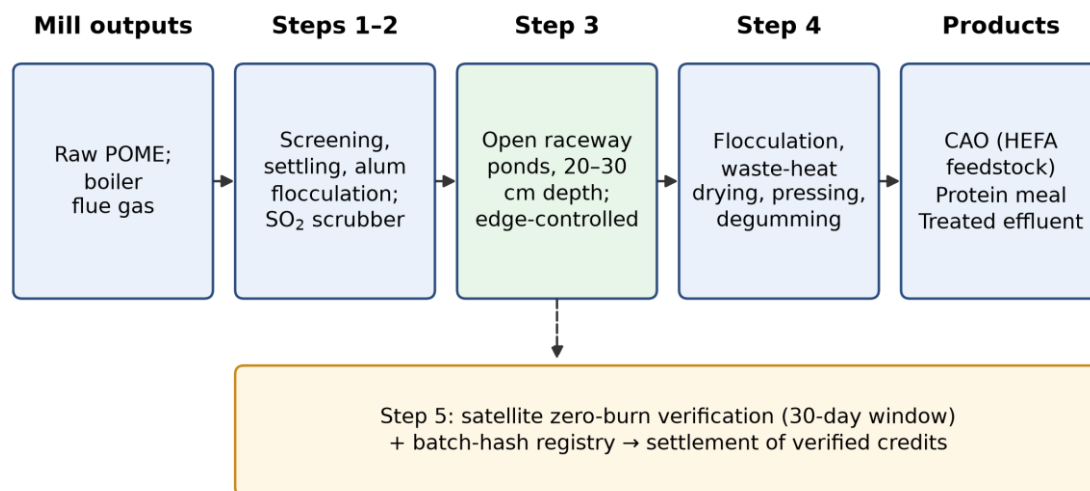
Macro, financial, legal, and compliance risks.

- *Double counting of credits.* Link satellite-verified zero-burn status to batch-level production logs through cryptographic hashes, and check every claim against registry records before issuance (Schneider et al., 2015).

- *Regulatory and community governance.* Comply with Law No. 32/2009 and the ASEAN Agreement on Transboundary Haze Pollution. Establish free, prior, and informed consent (FPIC) agreements and profit-sharing schemes with local communities.
- *Off-taker quality requirements.* Subject harvested CAO to centrifugal degumming and bleaching to meet the off-taker's feedstock limits (for example, ≤ 15 ppm total metals and phosphorus and $< 0.5\%$ free fatty acids). These limits are illustrative of off-taker requirements, not certification criteria; ASTM D7566 applies only to the finished, hydroprocessed jet fuel blend.
- *Cross-border data privacy.* Strip personally identifiable information at the edge, store operational data in Indonesia, and execute financial settlement in Singapore, in line with Singapore's PDPA 2012 and Indonesia's Law No. 27 of 2022.

A.5 Step-by-step implementation guide

Figure 6. Process flow of the five-step estate conversion



Note. Steps correspond to Steps 1 to 5 of Section A.5. The dashed arrow indicates that batch-level production logs from the ponds feed the verification and settlement step.

Step 1: Lagoon retrofitting and hydraulic engineering

1. *Pond re-engineering.* Convert four- to five-stage anaerobic POME lagoons into shallow open raceway ponds with a uniform depth of 20–30 cm.
2. *Baffling and lining.* Install HDPE liners (1.0–1.5 mm) and central divider baffles to maintain a uniform channel flow.
3. *Paddlewheels.* Mount locally fabricated four-blade paddlewheels driven by redundant gear motors powered by mill biogas generators and battery backup. Maintain a channel velocity of 0.2–0.3 m s⁻¹.
4. *Flue-gas scrubbing and sparging.* Pass boiler exhaust through an alkaline packed-tower scrubber to remove SO₂, then distribute it through PVC piping and 316L stainless steel spargers along the pond floor.

Step 2: Strain selection and effluent pre-treatment

1. *Pre-treatment.* Pass raw POME through a 200-mesh vibrating screen, an anaerobic settling trap, and an alum flocculator to remove heavy metals, coarse solids, and excess phenolics.
2. *Inoculation.* Inoculate with robust strains such as *Chlorella vulgaris* or *Arthrospira platensis* (Spirulina) adapted to 30–38 °C. Maintain PBR seed tanks for rapid recovery.
3. *Nutrient balance.* Use the nitrogen and phosphorus already present in POME as the nutrient source, supplementing only where analysis shows a deficit.

Step 3: Installing and calibrating Eagor-Core edge gateways

1. *Hardware.* Install a redundant edge pair in an IP65 enclosure at each pond cluster, for example, a single-board computer (Raspberry Pi 4) as the primary controller and an ESP32-based programmable logic controller as a watchdog and fallback. Policies deployed to the microcontroller should be distilled or quantized to fit its memory.
2. *Sensors.* Connect self-cleaning sensor arrays with mechanical wipers: redundant gel-filled pH probes (0–14), dual optical-density sensors (OD₆₈₀) for biomass, galvanic DO sensors, and waterproof PT100 temperature sensors.
3. *Drones.* Install a docking and charging station with one multispectral and one LiDAR drone, register the aircraft and remote pilots with the civil aviation authority, and define flight corridors over the pond grid and the estate boundary.

Step 4: Low-energy harvesting and refining

1. *Flocculation.* Use low-cost organic flocculants, or induce flocculation by raising pH under Eagor-Core control, to concentrate the slurry without energy-intensive centrifugation.
2. *Drying.* Dewater the biomass on solar drying beds assisted by boiler waste heat.
3. *Fractionation.* Extract lipids by mechanical pressing followed by centrifugal degumming to produce CAO for HEFA processing, and dry the residual biomass (typically 40–50% protein) for sale as aquaculture feed.

Step 5: Satellite zero-burn verification and settlement

1. *Registration.* Register the estate perimeter on the Eagor-Core registry with personal data removed.
2. *Verification and double-counting check.* The macro-layer ingests VIIRS and MODIS active-fire products and Sentinel-1 SAR imagery and cross-checks registry records (Section 4.6).
3. *Disbursement.* After 30 consecutive days without verified fire detections and with verified production records, smart contracts disburse credits to the multi-signature wallets of the estate and of the smallholder cooperative.

A.6 Simulator state variables and balance equations

Table A2 summarizes the state variables of the simulator and the structure of their balance equations, which complete the transition kernel P of the Dec-POMDP in Section 4.2.

Table A2. State variables and balance equations of the simulator

State variable	Balance equation (structure)	Main drivers
Biomass density B	$\frac{dB}{dt} = (\mu - m - D)B - \frac{q^{POME} + q^{rain} - q^{evap}}{V} B$	Light, temperature, pH, toxicity, dilution
Pond volume V	$\frac{dV}{dt} = q^{POME} + q^{rain} - q^{evap} - q^H$	Effluent feed, rain, evaporation, harvest
Dissolved inorganic carbon C	$\frac{dC}{dt} = \frac{\eta_{CO_2} q^{CO_2}}{V} + k_L a (C^* - C) - Y_C \mu B - \frac{q^{in}}{V} C$	CO ₂ injection, gas exchange, uptake
pH	Algebraic: carbonate equilibrium given C , alkalinity, and temperature	Inorganic carbon, alkalinity
Dissolved oxygen O	$\frac{dO}{dt} = Y_O \mu B - r_R B + k_L a_O (O^* - O) - \frac{q^{in}}{V} O$	Photosynthesis, respiration, mixing
Nitrogen N , phosphorus P	$\frac{dN}{dt} = \frac{q^{POME}}{V} (N_{in} - N) - Y_N \mu B \text{ (P analogous)}$	Effluent composition, uptake
Toxicity index χ	$\frac{d\chi}{dt} = \frac{q^{POME}}{V} (\chi_{in} - \chi) - k_\chi \chi$	Phenolics and metals in feed, degradation
Probe drift δ , fouling ϕ	Equations (6) and (7)	Calibration, backwash

Note. k_{LA} = gas–liquid mass-transfer coefficient, which increases with paddlewheel speed; Y = yield coefficients; η_{CO_2} = CO₂ transfer efficiency; r_R = respiration rate; asterisks denote saturation concentrations; $q^{in} = q^{POME} + q^{rain} - q^{evap}$ is the net dilution flow. Parameter values and their sources are released with the simulator code.

Appendix B. Policy Brief: Bilateral Co-Investment in a 10-Hectare Demonstration Facility

To: Ministry of Sustainability and the Environment (MSE), National Environment Agency (NEA), and Economic Development Board (EDB), Singapore

From: Lanz CWJ Chan (Finamatrix Quant-Lab, Singapore) and Shin-Hung Pan (Chaoyang University of Technology, Taiwan)

Subject: Bilateral co-sponsorship of a 10-hectare Eagor-Core demonstration facility in Indonesia to reduce transboundary haze

B.1 Rationale

Transboundary haze imposes recurring health and economic costs on Singapore that originate outside its jurisdiction (Koplitz et al., 2016; Glauber et al., 2016). Section 3 shows that conditional payments make non-burning privately rational only when verification is credible and the payment covers the cost advantage of fire. A demonstration facility would test, under field conditions, whether mill-level algae revenue and three-tier verification can meet that condition. This brief is based on a conceptual framework and assumption-based engineering estimates. It is not a field-validated investment proposal, and field performance and carbon benefits have not been demonstrated.

B.2 Bilateral alignment

Public health. Lower fire activity in participating estates reduces one source of haze affecting Singapore. The demonstration would measure the avoided burned area within participating geofences rather than claim regional elimination of haze.

Sustainable aviation fuel. Singapore has set a 1% SAF uplift target, with the SAF levy applying to flights departing from 1 January 2027, and aims to raise the target to 3–5% by 2030, subject to global developments (Civil Aviation Authority of Singapore, 2024, 2026). CAO from POME could supply HEFA feedstock if it meets refiner specifications and the sustainability criteria Singapore applies to SAF (Doliente et al., 2020).

High-integrity carbon credits. Singapore and Indonesia signed an MoU on carbon credits collaboration under Article 6 of the Paris Agreement on 6 July 2026 (Ministry of Trade and Industry, 2026). Satellite- and drone-verified zero-burn records linked to registry entries would allow credits from the facility to be checked against double-counting (Schneider et al., 2015).

Institutional fit. The MoU on Environmental Cooperation, signed on 29 June 2026, covers transboundary pollution, climate change, and joint pilot projects (Ministry of Sustainability and the Environment, 2026), providing a framework under which the demonstration could be endorsed.

B.3 Proposed phasing

The phasing follows Figure 5 and Section A.3: bilateral endorsement and a pilot module (months 1–6); a 10-hectare demonstration in Riau or Central Kalimantan with smallholder onboarding and drone and satellite verification (months 6–18); and private roll-out to other mills once the

demonstration meets its go/no-go criteria (months 18–36). The capital requirement of the demonstration is USD 439,300, and its annual operating cost is USD 93,000 (Tables 3 and 4).

B.4 Requests

We request (i) co-funding of the demonstration CAPEX, (ii) facilitation of a host-site agreement with the relevant Indonesian ministries and a participating mill, and (iii) agreement on data-sharing arrangements that comply with both countries' personal data protection laws (Republic of Indonesia, 2022; Republic of Singapore, 2012).