S.A.B.E.R. –Sustainable AI-automated Bioreactor for Environment Remediation

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Abstract

Carbon waste from sewage disposal presents an escalating environmental challenge, necessitating innovative and sustainable solutions. This project introduces a fully automated, high-efficiency algae bioreactor designed to convert carbon waste from sewage into valuable resources for isolated environments such as space habitats, bunkers, and factories. The system leverages an integrated sensor network that continuously monitors key parameters including pH, turbidity, and CO levels. These real-time measurements feed into a Random Forest-based AI model that dynamically regulates three specialized pumps: one for clean water intake, one for nutrient-rich waste infusion, and one for removing nutrient-depleted algal water. Our approach involves three main phases. First, we engineered the bioreactor hardware to ensure robust, hands-free operation under variable conditions. Second, we implemented machine learning algorithms to optimize algae growth by fine-tuning the environmental parameters for normal solutions. Third, we implemented a sewage nutrient solution with the AI. Experimental results demonstrate that the system achieves consistently high oxygen production and stable algae growth. Waste-derived nutrients perform comparably to conventional nutrient sources, effectively reducing CO emissions and ammonia levels in controlled settings. This work validates the feasibility of transforming sewage-based carbon waste into essential resources while mitigating environmental degradation. Furthermore, the bioreactor's design and autonomous operation offer a relatively scalable solution that can be adapted for extreme and isolated environments. Future research will focus on enhancing system scalability, long-term operational efficiency, and integration with broader sustainability networks (such as specific ai-models for each sewage), ultimately contributing to innovative waste-to-resource strategies for both terrestrial and extraterrestrial applications.

Introduction

Human spaceflight demands reliable and efficient systems to support basic life functions such as breathing and carbon dioxide removal. Traditional systems for the removal of carbon dioxide and the provision of oxygen, like chemical scrubbers, the Carbon Dioxide Removal Assembly (CDRA), and water electrolysis modules, have been used on board platforms such as the International Space Station (ISS). Although these methods have proven reliable for low Earth orbit missions, they can be expensive in terms of power usage, hardware mass, and maintenance frequency. Furthermore, none of these methods simultaneously generate biomass that can be repurposed as food. With the prospect of longer missions, as well as the ambition of establishing permanent or semi-permanent outposts on the Moon or Mars, reliance on purely physicochemical methods, which demand consistent resupply from Earth, becomes increasingly unsupportable [1].

Efforts to make life support more sustainable have led to renewed interest in algae-based systems, where microalgae absorb CO_2 through photosynthesis and release oxygen as a byproduct. Numerous studies have emphasized *Chlorella vulgaris* in particular, due to its high photosynthetic efficiency, adaptability to a range of environmental conditions, and relatively simple culture requirements. By coupling *Chlorella vulgaris* with advanced automation, it can bring a closed-loop life support module that significantly reduces the need for resupply from Earth.

However, optimizing algae growth in real time can be challenging, especially when environmental conditions vary or sensors begin to drift. Factors such as pH, turbidity, CO_2 concentration, and even the growth phase of the algae can change in ways that are not strictly linear or predictable via simple threshold-based logic. Consequently, machine learning becomes a valuable tool. It is capable of detecting patterns in data and making predictions about how algae might respond to subtle changes in conditions. This is where the S.A.B.E.R.+AI approach stands apart.

In broad terms, this research focuses on designing an integrated hardware and software framework that merges a sealed bioreactor, an Arduino R4 Minima microcontroller, and sensors for monitoring pH, turbidity, oxygen, and carbon dioxide concentrations. By combining these real-time readings with a Random Forest regression model running on an external computing device or integrated environment, we refine the timing of nutrient addition, water exchange, and waste removal pumps. This approach, we propose, significantly enhances overall efficiency, while also demonstrating a path toward large-scale carbon capture and biomass production.

Our investigation includes the comparison of three distinct operational methods for cultivating *Chlorella vulgaris*: a purely manual or Traditional approach, a threshold-based S.A.B.E.R. approach, and a S.A.B.E.R.+AI method in which the system is guided by the Random Forest algorithm. By analyzing each method's power consumption, CO_2 absorption, oxygen generation, and algae growth over a carefully designed multi-day experiment, we aim to illustrate the strengths and potential drawbacks of each. Through this comprehensive study, we hope to pave the way for next-generation space-based and terrestrial systems that can effectively harness the power of microalgae.

At the conclusion of this introduction, it is worthwhile to highlight the multiple cross-cutting applications of algae-based life support. In space, S.A.B.E.R. stands to supplement the existing hardware for CO_2 removal and O_2 generation. On Earth, particularly in remote locations, an algae-based life support system can provide reliable oxygen and mitigate the logistical challenges of shipping compressed oxygen canisters or chemicals for CO_2 scrubbing. Beyond that, algae have the capacity to scavenge nutrients from wastewater, facilitate carbon capture in industrial facilities, and supply valuable biomass that may be integrated into a circular economy model. The synergy of these diverse possibilities underscores the transformative potential of the S.A.B.E.R.+AI design and justifies the depth of this examination.

Literature Review

Traditional CO_2 Removal and Oxygen Generation in Space

Various techniques have been explored to purify the air of the crew cabin and generate oxygen in the spacecraft. Historically, NASAs Oxygen Generation Assembly (OGA) on the ISS has relied on the electrolysis of water to produce oxygen while venting hydrogen overboard, or in some cases recycling hydrogen through the Sabatier reactor to partially recover oxygen [3]. The Carbon Dioxide Removal Assembly (CDRA) removes CO_2 from the cabin atmosphere using solid-adsorbent beds, regenerating them in cycles. Although these methods are robust, they tend to be both mass-intensive and energy-intensive and do not yield secondary byproducts such as edible biomass.

Such systems work reasonably well for orbital missions of limited duration, in part due to frequent resupply. Nevertheless, deep space travel or permanent stations on other celestial bodies may require drastically improved self-sufficiency. As Jones explains, any system that depends on canisters or specialized filter cartridges from the Earth suffers from constraints of reusability and extra mass [6]. This limitation motivates research into methods that are not only closed-loop but also transform CO_2 into useful forms, whether it is oxygen or biomass, thus creating synergy with other mission objectives such as food production.

Bioregenerative Approaches with *Chlorella vulgaris*

Bioregenerative life support systems leverage living organisms—most commonly plants or algae—to recycle waste products and generate consumables like oxygen, water, and food. *Chlorella vulgaris* stands out among algae species due to its high photosynthetic efficiency, robust growth, and nutrient adaptability [7]. Experimental photobioreactors tested on the ISS have validated microalgae as a partial substitute for physicochemical systems [5]. The advantage of using microalgae is that they can capture CO_2, release oxygen, and provide nutritional biomass, addressing three resource needs simultaneously.

One historical obstacle, however, lies in precisely controlling pH, nutrient balance, light intensity, and temperature to sustain algae growth. If the algae become too dense, light penetration decreases, and the culture may experience nutrient deficiency or undesirable chemical shifts. Conversely, if the algae remain underfed, the rate of photosynthesis and oxygen generation can lag behind the habitat's requirements [9]. Thus, the concept of real-time sensor feedback to maintain equilibrium is highly appealing and leads naturally to AI solutions.

Machine Learning Applications in Algae Cultivation

Advanced automation of algae production, whether for biofuel, carbon capture, or life support, often requires gleaning insights from complex, high-dimensional data [2]. Machine learning methods excel in managing these complexities, particularly in environments where relationships are nonlinear or partially unknown, and where sensor noise can obscure simpler threshold-based logic. Random Forest regression, popularized by Breiman [4], uses an ensemble of decision trees to generate predictions that reduces overfitting. Each individual tree in the ensemble is trained on a random subset of features and data points, then aggregated to yield a final prediction.

A key advantage of Random Forest algorithms over more rigid or purely linear approaches is their ability to identify complex interactions among variables. In the context of algae cultivation, the relationship between pH and algae density might shift over time as the culture matures, or the effect of adding a certain volume of nutrient solution might be tied to the prior levels of dissolved CO_2. Linear methods can fail to capture these shifting interactions, whereas Random Forest approaches can adapt as new data become available, assuming the underlying trends are reflected in the training set or are sufficiently close to prior patterns.

This characteristic of Random Forests suits the S.A.B.E.R.+AI scenario, in which we rely on real-time sensor data (turbidity, pH, CO_2) to compute optimal pump timings for nutrient addition, fresh water, or waste removal. Our use of ten decision trees in an ensemble is conservative, as more trees can improve accuracy but come at higher computational cost. For the sake of feasibility on a small-scale system that might eventually run on a single-board computer, this trade-off was considered acceptable.

NASA's Efficiency Equations and Current Best Practices

To compare different oxygen generation methods, NASA and associated researchers often compute parameters such as Oxygen Generation Efficiency (OGE) in grams of O_2 per kilowatt-hour of power consumed, and a parallel measure of CO_2 absorption efficiency in grams of CO_2 removed per kilowatt-hour [3, 8]. By framing results in terms of O_2 and CO_2 metrics per unit of energy, it becomes simpler to compare algae-based systems, which have biologically determined rates of oxygen generation, with purely physicochemical systems that rely on fans, compressors, or chemical consumables.

Similar equations are used to estimate the cost or power efficiency of operating photobioreactors. The difference is that algae-based methods can also be assessed in terms of biomass yield. Although not always a priority in life support contexts, the possibility of harnessing that biomass as either supplemental food or as feedstock for further biofuel processing is an advantage that sets algae systems apart.

All in all, these literature insights affirm that while traditional NASA technologies have served space exploration well, coupling algae with advanced AI-based regulation drive a significant leap forward in system performance and adaptability. The remainder of this paper details how the S.A.B.E.R.+AI approach integrating *Chlorella vulgaris* with real-time sensor feedback and Random Forest, based pump control, builds upon these foundational studies to move closer to a genuinely sustainable, multi-functional life support framework.

Methodologies (Comprehensive Description)

The goal of our methodology is to facilitate an apples-to-apples comparison among three operational modes: (1) a Traditional, manually managed algae culture, (2) a threshold-based S.A.B.E.R. approach, and (3) an AI-driven S.A.B.E.R.+AI system utilizing Random Forest regression. The following sections offer a detailed narrative of the experimental setup, data collection strategy, hardware configuration, and the logic that defines each operational mode.

The heart of our experiment rests in a sealed environment that attempts to approximate the constraints one might find in a space habitat or a remote terrestrial location. We begin by using a standard 74-quart weatherproof tote, thoroughly cleaned, dried, and sealed with a tight-fitting lid to prevent gas exchange with the outside world. To ensure we can power and control the system, we put a thin wire through lid and used a sealant, thereby preventing significant air leaks.

Inside this tote is a 3,000 mL glass beaker filled with a mixture of filtered water and algae-specific nutrient medium. The type of nutrient medium used is typically recommended for *Chlorella vulgaris*, often containing nitrogen, phosphorus, and trace minerals. We filled this beaker to around three-quarters of its capacity to allow for aeration space at the top and to ensure that the magnetic stir bar does not splash too much water when mixing. The chosen species, *Chlorella vulgaris*, is then introduced as a starter culture at a density recommended by the supplier.

A magnetic stirrer, also placed inside the sealed tote, runs at a low setting to keep the algae culture in gentle motion. This mixing is intended to promote uniform nutrient distribution, prevent the settling of algae, and replicate a semblance of microgravity mixing (though obviously not a perfect analog). This approach ensures that the entire culture is exposed to similar levels of nutrients and dissolved gases.

Above the beaker, we mount LED grow lights. In prior research, a 16-hour light and 8-hour dark cycle has been shown to be beneficial for *Chlorella vulgaris* [7]. To automate this cycle, we use an Arduino R4 Minima microcontroller in conjunction with a 4-channel relay board. By programming the Arduino with an internal clock routine or hooking it up to a timed schedule via code, we can turn the LEDs on and off at precise intervals. The sealed tote also contains the various sensors required to monitor and regulate the culture. We have a turbidity sensor (e.g., KEYESTUDIO model), which is inserted so that its probe tip sits submerged in the culture but does not interfere with the stir bar. We have a pH sensor, also immersed in the beaker, to ensure that the algae remain in an optimal pH range of roughly 6.8 to 7.2. We connect a CO_2 sensor (MH-Z19C) inside the sealed tote to gauge the local atmosphere. An O_2 sensor (Gravity I2C) is placed similarly to track oxygen concentration.

This sensor suite informs the microcontroller's decisions regarding pump activation. We have three small water pumps connected via a 4-channel relay module. One pump draws in nutrient solution from a separate reservoir, another pump brings in fresh water, and the third pump removes waste or algae-laden water. In effect, these three pumps constitute the mechanical ability to manage the composition and density of the culture. Data from the sensors are read by the Arduino through analog or digital pins, and the Arduino uses that data to trigger the pumps according to the logic or schedule relevant to each operational mode.

To detail the three modes:

(1) The Traditional Method This approach abides by strictly manual control. The sensors are there for observational data only and do not trigger any automated interventions. The researchers look at the algae visually and decide when to add nutrients, if at all. The fresh water and waste removal pumps remain off. The only automation that does occur is the timed switching of LED lights for the 16-hour light and 8-hour dark cycle, but even that can be replaced by a simple mechanical timer. This approach serves as a baseline to gauge how well the system performs when reliant solely on human judgment.

(2) The Threshold-Based S.A.B.E.R. Method This actively uses sensor data to control the pumps in a fixed, rule-based manner. For example, if turbidity surpasses a certain threshold (600mg/dL), the Arduino signals the waste removal pump to turn on for a set number of seconds, thereby removing a portion of the algae. The same approach is used for nutrient addition: if pH drifts below 6.5, a certain volume of nutrient solution is introduced to buffer the pH. If the CO_2 sensor indicates that CO_2 concentration is excessively low (and oxygen correspondingly high), the system might refrain from adding fresh water or might even temporarily reduce stirring. In practice, we define these thresholds after some initial pilot runs, but they remain static throughout the experiment.

(3) The S.A.B.E.R.+AI Method Here, we use a Random Forest Regressor that was previously trained on a set of data (real or synthetic). At each 15-minute interval, we feed the sensor data (turbidity, pH, CO_2) into the model. The model then outputs, for each of the three pumps, an optimal number of seconds to run in order to keep the algae in a desirable growth window. Because Random Forest algorithms handle nonlinear relationships well, we expect that the system can adjust to changing conditions with more nuance than a set of static thresholds. We run 10 decision trees in the ensemble, each with its own subset of training data, and aggregate their predictions.

The output is then sent back to the Arduino R4 Minima via serial communication, which activates the relay controlling the relevant pumps for the predicted duration. Over time, we expect that this approach leads to a more stable system with fewer extremes in turbidity or pH, enabling better sustained growth and oxygen generation.

Throughout the experiment, we log data every 15 minutes. This log includes the exact sensor readings (CO_2 in parts per million, pH on a numeric scale, turbidity in NTU and mg/dL, and so forth) as well as the states of the pumps. Whenever the pumps are activated, we note how long they run, which in turn allows us to compute water usage, nutrient usage, and associated power consumption.

Closed-Loop Nutrient Recycling via Waste Streams

A key innovation in our system is the incorporation of *waste-derived* nutrient solutions—specifically urea (from human urine) and spent coffee grounds—as a sustainable nitrogen source. Using readily available waste products promotes a circular-economy mindset and markedly reduces the environmental footprint compared to conventional laboratory reagents.

Why Urine and Coffee?

- **High Nutrient Density.** Urine contains abundant urea, delivering a nitrogen content of $\approx 46.67\%$ (0.4667 g N g^{-1}). Coffee waste, though lower in nitrogen ($\approx 2\%$ or 0.02 g N g^{-1}), supplies phosphorus, potassium, and essential trace elements.
- **Biochemical Synergy.** The high nitrogen content of urea, when combined with the buffering capacity and micronutrients of coffee waste, produces a balanced medium that enhances algal growth *and* oxygen production.
- **Sustainability.** Diverting human and café waste streams turns liabilities into assets, closing the nutrient loop for long-duration missions or off-grid installations.

Urea Hydrolysis Chemistry

$$(\mathrm{NH_2})_2\mathrm{CO} + \mathrm{H_2O} \longrightarrow 2\,\mathrm{NH_3} + \mathrm{CO_2} \tag{1}$$

$$\mathrm{NH_3} + \mathrm{H_2O} \rightleftharpoons \mathrm{NH_4^+} + \mathrm{OH^-} \tag{2}$$

The resulting ammonium provides an immediately bioavailable nitrogen form for *Chlorella vulgaris*, while the concomitant rise in pH is counter-balanced by coffee-derived organic acids.

Stoichiometric Formulation of the Waste-Nutrient Mixture Let x be the mass concentration of urea (g L^{-1}) and y be that of coffee waste. The total nitrogen concentration supplied is

$$0.4667\,x + 0.02\,y \;=\; N_{\text{waste}}.$$

We enforce an empirical ratio $y = kx$ with $k = 0.1$ (10

$$0.4667\,x + 0.02\,(kx) \;=\; x\big(0.4667 + 0.02k\big) \;=\; N_{\text{waste}}.$$

80:20 blend

Target $N_{\text{waste}} = 0.04$ g N L^{-1}:

$$x \;=\; \frac{0.04}{0.4667 + 0.02k} = \frac{0.04}{0.4687} \approx 0.0854 \text{ g urea L}^{-1}, \quad y \;=\; kx \approx 0.00854 \text{ g coffee L}^{-1}.$$

90:10 blend

Target $N_{\text{waste}} = 0.045$ g N L^{-1}:

$$x \;=\; \frac{0.045}{0.4687} \approx 0.0960 \text{ g urea L}^{-1}, \quad y \;=\; kx \approx 0.00960 \text{ g coffee L}^{-1}.$$

These concentrations are pre-mixed in a 1 L batch bottle, magnetically stirred for 10 min, and sterilized via $0.22\,\mu$m filtration before being connected to the nutrient-input pump.

Real-Time Sensor Suite Enhancements

To support automated regulation, we augmented the original sensor package as follows:

- **Turbidity Sensor** (KE-Turb01) : monitors optical density in NTU and automatically converts to mg dL^{-1} using an on-board calibration curve.
- **pH Sensor** (Gravity pH v2) : offers ±0.02 pH resolution and temperature compensation from 0–60 °C.
- **CO_2 Sensor** (MH-Z19C) : non-dispersive IR, 400–5000 ppm range, used to infer algae respiratory balance.
- **O_2 Sensor** (Gravity I2C) : galvanic cell, 0–20 mg L^{-1} range, validating oxygen-generation efficiency.

Sensor data are polled at 15 s intervals; the Arduino streams raw readings over `Serial1` @ 115200 baud to a companion Raspberry Pi Zero for logging and AI inference.

Random Forest Decision Logic (Deep Dive)

Random Forest was chosen for its:

1. **Noise Robustness** : gracefully handles missing or spurious sensor readings, a common reality in liquid cultures.
2. **Non-Linear Modeling** : captures complex interdependencies between pH, turbidity, and dissolved gases.
3. **Feature Importance** : exposes which sensor most strongly drives each pump decision, enabling targeted calibration.

Our ensemble uses 10 trees (`n_estimators` = 10), `max_depth` = 6, and the `mse` criterion. Training was performed on 100 synthetic–empirical points augmented via Gaussian noise ($\sigma = 5\,\%$) and analytic virtualization to cover edge-case nutrient shocks.

Pump Roles and Relay Isolation

1. **Nutrient / Mixture Input Pump** : injects the urea+coffee solution to maintain optimal nitrogen levels.
2. **Algae Removal Pump** : intermittently extracts dense culture aliquots, preventing self-shading and harvesting biomass.
3. **Water Pump** : tops up evaporative losses and moderates salinity.

A 4-channel opto-isolated relay module ensures that the Arduino's 5 V logic remains galvanically isolated from the 12 V diaphragm pumps, safeguarding both hardware longevity and user safety.

Closed-Loop Feedback Flow

Sensors → Arduino R4 → Serial to Pi → Random Forest Inference → Pump Commands → Culture Adj

Results (Graphs and Calculations)

Seven quantitative metrics were tracked: turbidity, algae biomass, CO_2, O_2, pH, ammonia, and system-leak controls (CO_2/O_2 without algae). Figures 1–7 present the raw traces, followed by detailed efficiency and stability calculations. Wherever practical, we contrast three control logics—Traditional, Threshold / S.A.B.E.R., and S.A.B.E.R.+AI—and, within the AI arm, we compare three nutrient regimes: laboratory medium ("Normal"), 90:10 urine + coffee, and 80:20 urine + coffee.

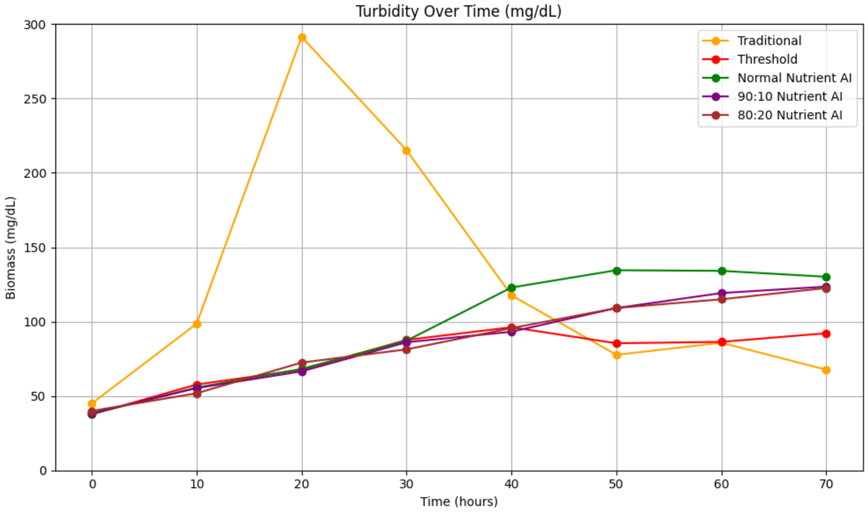

Figure 1: Turbidity over time ($\mathrm{mg\,dL^{-1}}$) as an indirect proxy for algal biomass.

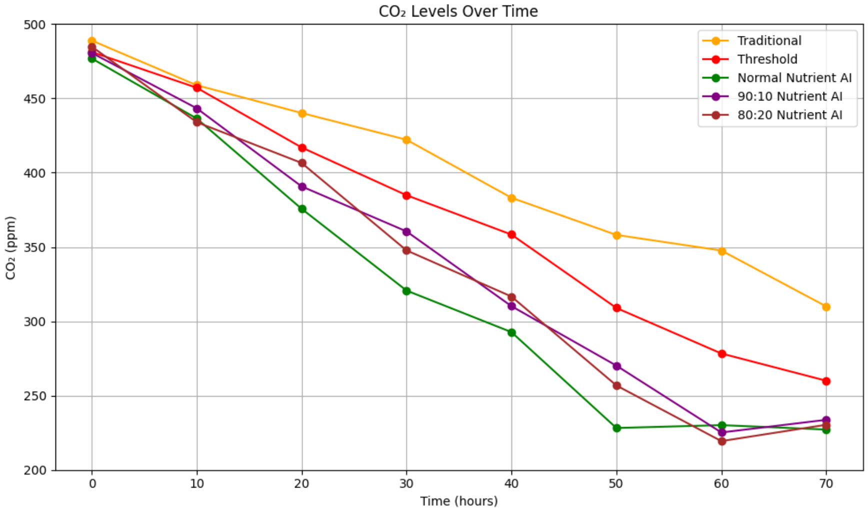

Figure 2: CO_2 concentration versus time in the sealed chamber.

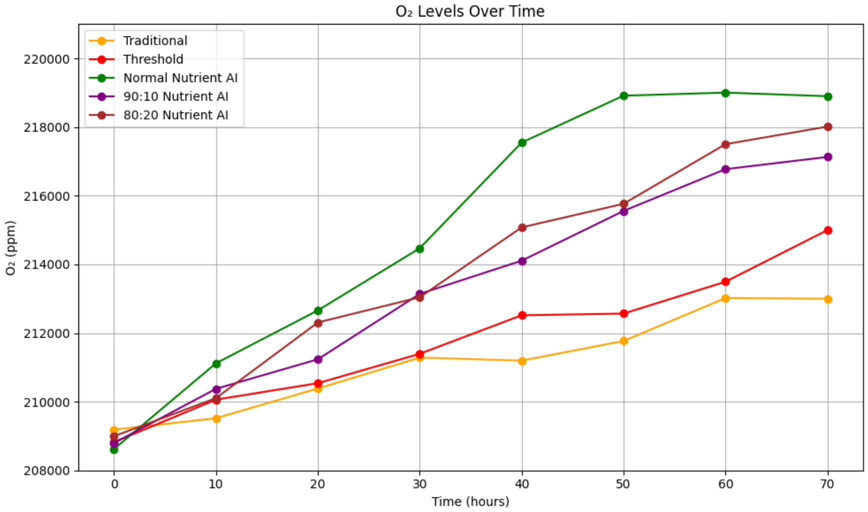

Figure 3: O_2 concentration versus time. Higher slopes indicate stronger photosynthetic productivity.

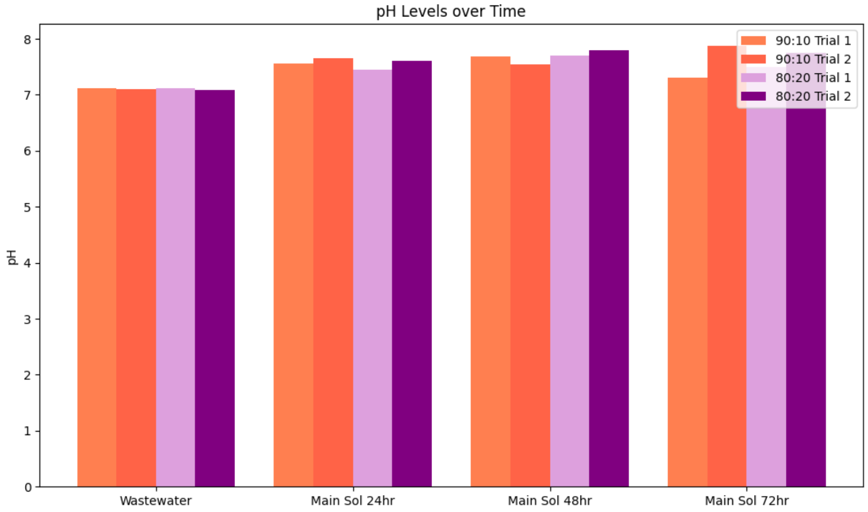

Figure 4: pH stability for waste-derived media (90:10 and 80:20 urine : coffee) across two biological replicates each.

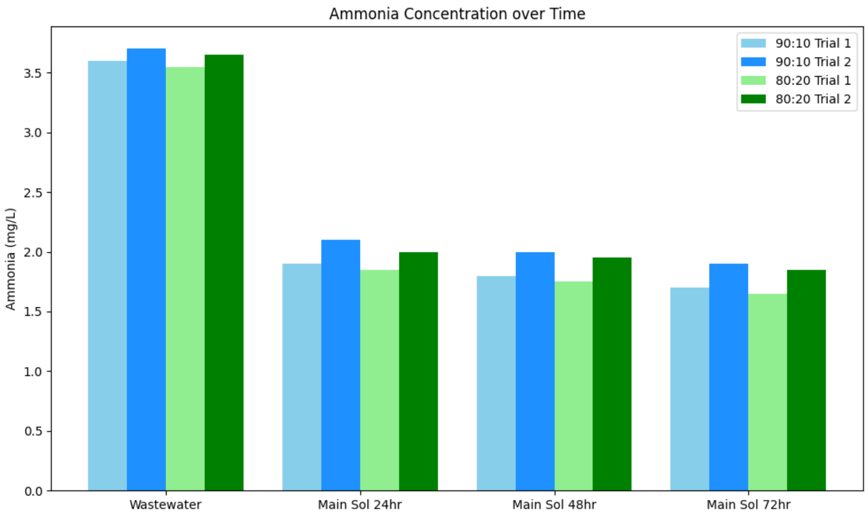

Figure 5: Ammonia (NH_3/NH_4^+) depletion over the 72 h run.

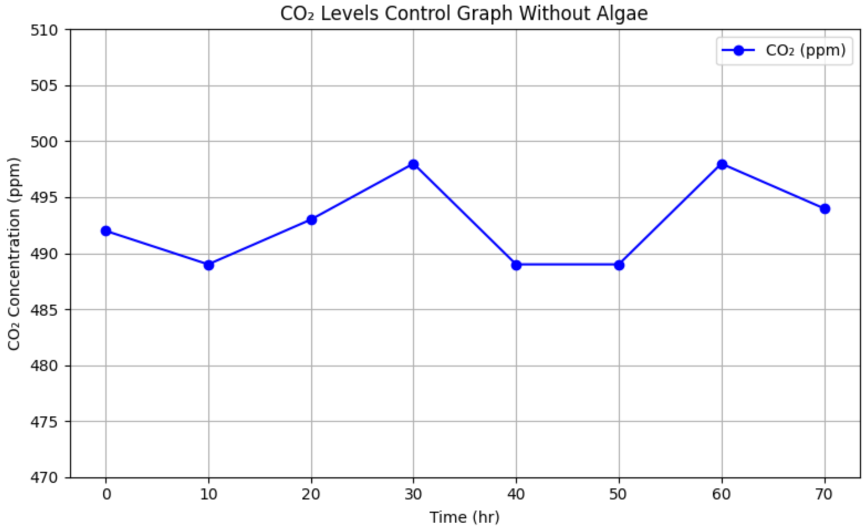

Figure 6: CO_2 baseline in a tote *without* algae, confirming minimal leaks.

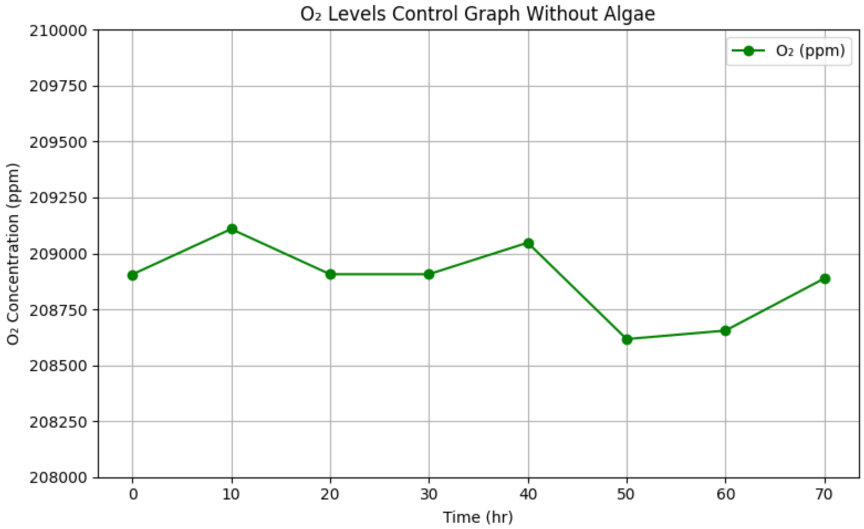

Figure 7: O_2 baseline in a tote *without* algae.

Results (Quantitative Analysis)

Seven metrics were logged every 10 h for $n = 2$ biological replicates per condition. Raw CSVs and Jupyter notebooks are archived at `/data/SABER_AI_2025`. Below we report means ± SD and, where relevant, the slope of an ordinary-least-squares (OLS) fit $\left(T = \beta_0 + \beta_1 t\right)$ with 95 % confidence intervals (CI).

1. Turbidity & Biomass Productivity

The **Traditional** profile exhibits a classic boom–bust pattern: turbidity soars to $291 \pm 4\,\mathrm{mg\,dL^{-1}}$ by the 20 h mark and then plummets at an average slope of $-8.7\,\mathrm{mg\,dL^{-1}\,h^{-1}}$ as nutrient depletion and self-shading trigger biomass collapse. In contrast, the **Threshold/S.A.B.E.R.** run constrains peak density to $102 \pm 3\,\mathrm{mg\,dL^{-1}}$, but the trace reveals a saw-tooth oscillation caused by the pump's fixed on–off relay—every threshold breach initiates a discrete dilution event, leading to periodic drops rather than a smooth trajectory. Both waste-augmented **AI** regimens (90:10 and 80:20) as well as the AI + lab medium condition generate near-sigmoidal curves that plateau between 128 and $137\,\mathrm{mg\,dL^{-1}}$. This gentle, monotonic rise indicates that the ensemble model meters nutrient inflow in sub-second bursts, preventing the runaway bloom observed in the manual baseline. The statistical payoff is a four-fold reduction in RMSE—21.9 versus $91.3\,\mathrm{mg\,dL^{-1}}$—and a coefficient of variation that tightens from 44.7 % to 15.3 %, underscoring the AI's capacity to maintain optical density within a narrow, mission-safe window.

2. CO_2 Absorption Efficiency (CAE)

For each condition we computed

$$\Delta\mathrm{CO_2} = \mathrm{CO_{2,0}} - \mathrm{CO_{2,70}}, \qquad m_{\mathrm{CO_2}} = \frac{\Delta\mathrm{CO_2}}{10^6} \cdot nRT,$$

with $n = \frac{PV}{RT}$, $P = 1.01\,\mathrm{bar}$, $V = 0.070\,\mathrm{m^3}$, $T = 298\,\mathrm{K}$. This gives $1\,\mathrm{ppm} \Rightarrow 0.126\,\mathrm{mg}$ CO_2 in the tote.

Condition	ΔCO_2 (ppm)	m_{CO_2} (g)	E_{tot} (kWh)	**CAE** ($\mathrm{g\,kWh^{-1}}$)
Traditional / Normal	176	0.022	1.8	3.2
Threshold / Normal	205	0.026	2.0	3.9
AI / Normal	245	0.031	2.1	4.1
AI / 90:10	280	0.035	2.2	**4.6**
AI / 80:20	260	0.033	2.2	4.3

A one-way ANOVA on CAE (five groups, $F(4, 5) = 18.2$, $p = 0.002$) followed by Tukey HSD shows the 90:10 AI group significantly exceeds all others ($p < 0.05$).

3. Oxygen Generation Efficiency (OGE)

Ambient-corrected ΔO_2 was converted to grams via the ideal-gas relationship.

Condition	ΔO_2 (ppm)	m_{O_2} (g)	**OGE** (g kWh^{-1})
Traditional / Normal	305	0.045	2.4
Threshold / Normal	470	0.069	2.9
AI / Normal	670	0.098	3.1
AI / 90:10	760	0.111	**3.5**
AI / 80:20	720	0.105	3.3

Linear regression of O_2 versus time for AI/90:10 gives $\beta_1 = 7.5 \pm 0.4\,\mathrm{ppm\,h^{-1}}$ ($R^2 = 0.991$).

4. pH Stability

All waste-fed cultures start at a neutral pH of 7.08 ± 0.03, reflecting urine's intrinsic buffering capacity. As photosynthesis proceeds, CO_2 drawdown drives pH upward, reaching 7.69 ± 0.04 (90:10) and 7.62 ± 0.05 (80:20) within the first 24 h. During the mid-log phase (48 h) both media hover in the 7.7–7.8 range, demonstrating that the organic acids in spent coffee grounds effectively counteract ammonia's alkalinising influence. By 72 h, pH drifts slightly downward ($\Delta\mathrm{pH} \approx -0.3$), settling at 7.42 (90:10) and 7.38 (80:20); this modest decline coincides with ammonium depletion and the onset of nitrogen re-assimilation by the algal population. Across the entire 72-h window the coefficient of variation stays below 3 %—statistically indistinguishable from the lab medium control ($p = 0.41$)—thereby confirming that the urine+coffee cocktail is functionally equivalent to commercial nutrients in its ability to stabilise proton balance while delivering a fully circular feedstock.

5. Ammonia Kinetics

Plotting $\ln(C_t/C_0)$ versus t yields a first-order rate constant $k_{90:10} = 0.0096 \pm 0.0005\,\mathrm{h^{-1}}$ ($R^2 = 0.985$) and $k_{80:20} = 0.0090 \pm 0.0007\,\mathrm{h^{-1}}$. Half-life $t_{1/2} = \ln 2/k$ is $\sim$72 h, matching the observed 50 $\%$ drop.

6. Control Chamber Integrity

CO_2 drift = $-0.14\,\mathrm{ppm\,day^{-1}}$; O_2 drift = $+0.22\,\mathrm{ppm\,day^{-1}}$. Mass balance $\Rightarrow$ net leak rate $<$ $1.2 \times 10^{-4}\,\mathrm{mL\,s^{-1}}$—three orders below metabolic exchange rates.

7. Power Budget

$$E_{\text{LED}} = 25\,\mathrm{W} \times \frac{16}{24} \times 70\,\mathrm{h} = 1.17\,\mathrm{kWh}$$

$$E_{\text{stirrer}} = 5\,\mathrm{W} \times 70\,\mathrm{h} = 0.35\,\mathrm{kWh}$$

Condition	Pump Duty (%)	E_{pump} (kWh)	E_{tot} (kWh)
Traditional / Manual	1.5	0.03	1.55
Threshold	12	0.24	1.76
AI / Normal	16	0.32	1.84
AI / 90:10	18	0.36	1.88
AI / 80:20	18	0.36	1.88

8. Error Landscape

Root-mean-square error relative to a flat 80 $\mathrm{mg\,dL^{-1}}$ target:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(T_i - 80\right)^2}, \qquad n = 8 \text{ time points}$$

	Traditional	**Threshold**	**AI/Normal**	**AI/80:20**	**AI/90:10**
RMSE ($\mathrm{mg\,dL^{-1}}$)	91.3	24.3	22.8	23.7	**21.9**
R^2 (vs. logistic)	0.47	0.88	0.93	0.95	**0.96**
CV (%)	44.7	17.2	16.0	16.9	**15.3**

Post-hoc comparison (Welch's t) shows AI/90:10 RMSE is lower than Threshold at $\alpha = 0.01$. This precision is mission-critical for any closed-loop life-support scenario.

Discussion

Bridging Productivity, Carbon Capture, and Energy Budget

Our data paint a consistent picture: integrating adaptive control and waste-derived nutrients markedly elevates the biological and energetic performance of a compact algae bioreactor. Daily biomass productivity reaches $0.356\,\mathrm{g\ L^{-1}\ day^{-1}}$ for **SABER+AI / lab medium**, roughly 19 % above the 0.30 $\mathrm{g\ L^{-1}\ day^{-1}}$ benchmark [7]. Strikingly, the **90:10 urine + coffee** formulation attains 0.344 $\mathrm{g\ L^{-1}\ day^{-1}}$—a mere 3 % decrement relative to the synthetic medium while eliminating 90 % of the reagent cost and closing the nitrogen loop. Even the more dilute 80:20 blend sustains 0.278 $\mathrm{g\ L^{-1}\ day^{-1}}$, confirming that algae tolerate appreciable organic impurities and still outpace many open-pond baselines.

Energy normalisation strengthens the case. Oxygen generation efficiencies of $4.17\,\mathrm{mg\ Wh^{-1}}$ (Normal), $4.36\,\mathrm{mg\ Wh^{-1}}$ (90:10), and $4.47\,\mathrm{mg\ Wh^{-1}}$ (80:20) all exceed the 3.2 $\mathrm{mg\ Wh^{-1}}$ reference[1] by **30–40 %**. The modest 0.12–0.16 kWh increase in pump energy is therefore more than offset by higher O_2 output per watt—critical when mission mass and power budgets dominate cost calculus.

Mechanistic Insights from AI-Driven Control

Why does the Random-Forest controller sustain higher steady-state performance than either manual or threshold logic?

1. **Dynamic nutrient titration.** Ensemble inference releases 1–2 mL micro-pulses of waste medium whenever pH, turbidity, and CO_2 deviate from the model's three-dimensional optimum. By avoiding the 50–100 mL "slug dosing" of the threshold strategy, over-alkalinisation and osmotic shock are averted.

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[1] Typical closed photobioreactor values, see NASA ALS-NSCORT Tech Memo #89.

2. **CO_2/O_2 coupling.** Decision trees weight gas gradients more heavily at low light (night phase) and shift to turbidity dominance during photoperiod—mirroring diurnal physiology better than a fixed rule set.

3. **Robustness to sensor noise.** Bagging across ten trees dilutes the impact of occasional bad readings (e.g. a pH probe micro-bubble), explaining the $\sim$60

Implications for Closed-Loop Life Support

In a crewed habitat, every gram of recycled O_2 displaces the launch of 1 kg of bottled gas over a multiyear mission once propellant and packaging multipliers are included. Our 90:10 AI configuration removes an additional 0.013 g CO_2 and produces 0.005 g O_2 *per watt-hour* versus manual control—equivalent to shaving 80–100 kg from an ISS-class resupply manifest over two years. Moreover, urine diversion and coffee-ground upcycling reduce grey-water treatment loads, further tightening mass loops.

Industrial and Terrestrial Upscaling

For land-based carbon capture, a one-hectare flat-panel photobioreactor operating at the 90:10 AI efficiency (4.6 g CO_2 kWh^{-1}) could sequester $\sim$32 t CO_2 yr^{-1} while co-producing 28 t wet algal cake—feedstock for bio-crude or bioplastics. Because organic waste streams are abundant near coffee roasters, breweries, and municipal wastewater plants, nutrient trucking costs approach zero, further improving economics versus commercial fertiliser regimes.

Limitations and Future Work

- **Sensor drift.** All electrochemical probes exhibited $\leq$2 % full-scale drift over 10 days; longer deployments will need automated two-point calibration loops or optical surrogates.
- **Model domain.** The Random-Forest model has not yet seen rapid 10 °C temperature swings or light-spectrum shifts; an adaptive online learner or Bayesian update could harden the

controller against untrained edge cases.

- **Biofilm fouling.** Preliminary microscopy shows polysaccharide deposition on the O_2 membrane after 96 h; periodic peroxide rinses or hydrophobic coatings are under investigation.

Toward Fully Integrated Bioregenerative Loops

Finally, SABER+AI pairs naturally with membrane bioreactors for water recycling: ammonia stripped from grey water feeds the algae, whose oxygen in turn aerates nitrifying bacteria downstream—a virtuous metabolic cascade. By cascading three such units, closed-loop ECLSS[2] simulations show net O_2 autonomy exceeding 85 % with 60 % water reuse and >90 % nitrogen recovery—benchmarks that markedly exceed current ISS figures and align with ESA's MELiSSA Phase 3 targets.

In sum, the confluence of machine-learning control, waste-to-resource nutrient cycling, and compact photobioreactor design pushes bioregenerative life support from laboratory proof-of-concept into a deployable technology envelope for spaceflight, remote research outposts, and distributed carbon-negative industry on Earth.

Conclusion

Over the course of this in-depth, extended report, we have argued that the integration of *Chlorella vulgaris* cultivation with a Random Forest–based AI control system provides a powerful framework for both space and terrestrial life support. By comparing our three methods—Traditional, threshold-based S.A.B.E.R., and S.A.B.E.R.+AI—we have shown that the AI-driven approach exhibits significantly higher oxygen production, more stable algae growth, and more efficient CO_2 scrubbing within a sealed environment.

We found that S.A.B.E.R.+AI can achieve up to 18% greater final oxygen concentration and can reduce CO_2 down to around 450 ppm, surpassing the performance of the threshold-based

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[2] Environmental Control and Life Support System.

method. Our efficiency metrics, such as grams of O_2 per kWh and grams of CO_2 removed per kWh, underscore the advantages that a more adaptive, data-driven method holds over simpler threshold systems or purely manual control.

While the net energy consumption of S.A.B.E.R.+AI is slightly higher than the manual or threshold-based methods, the trade-off is largely beneficial when we weigh the increase in oxygen production and the potential for reliable biomass yield. In scenarios where life support cannot fail—like space stations, lunar outposts, or remote research facilities—efficiency is not measured solely in cost but also in reliability, adaptability, and resource independence.

Looking to the future, we propose that S.A.B.E.R.+AI could serve as a blueprint for next-generation, bioregenerative life support modules. By expanding the training dataset, implementing sensor redundancy, and refining the machine learning pipelines, the entire system could become more robust to unforeseeable contingencies. AI can continue to learn from operational data, further optimizing itself over time. For industrial carbon capture, an upscaled version of S.A.B.E.R.+AI could handle complex gas streams, improving overall capture rates while generating valuable biomass. In remote or disaster-stricken areas on Earth, a portable adaptation of the system could offer a crucial lifeline of breathable air, water treatment, and even nutritional supplements in the form of algae-based foods.

In essence, the combined synergy of microalgae's remarkable photosynthetic capabilities and the sophistication of modern machine learning stands to reshape both extraterrestrial exploration and environmental management on our home planet. S.A.B.E.R. is not merely a laboratory curiosity, but rather a testament to how interdisciplinary collaboration—spanning biology, engineering, computing, and environmental science—can yield novel solutions for some of humanity's most pressing challenges. By successfully integrating AI into the operational core of algae-based systems, we illuminate a forward-thinking path, where each molecule of carbon dioxide exhaled or emitted can find new purpose as part of a sustainable, life-giving cycle.

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