RESEARCH PAPER

Modeling Approaches to Mitigate the Adverse Impact of Elevated CO_2 Levels on Agricultural Productivity

[1]Bhavani K (Research Scholar), [2]Dr.P. Vinayagam (Author)

[1, 2] Dr. MGR Educational and Research Institute, University,

Chennai, Tamil Nadu, India.

Abstract- *Increased levels of carbon dioxide (CO 2) in the atmosphere, which are a major factor in causing climate change, pose a wonder in the agricultural sphere, since at high atmospheric CO 2 levels, euphoria is possible, but at the same time the situation can lead to physiological stress, changes in quality, and the use of resources. This research puts forward an entire modelling system whereby the deleterious effects of high CO 2 concentrations on agricultural output have been quantitatively recorded and neutralized. With the joint work of crop growth simulation, resource optimization, and predictive analytics, we consider the consequences of CO 2 fluctuations in the major phases of crop development about different environmental and management circumstances. Multi-objective genetic algorithms meet climate-crop interaction models to help in determining the most feasible approaches to CO 2 dosing. Results of a simulation are exhibited with hardly any difference in complaints about yield stability, water use efficiency, and wastage of inputs when CO 2 is being managed optimally. The research provides input into sustainable, climate-smart agriculture through making it possible to decide adaptively under atmospheric uncertainties.*

Keywords: *CO_2 impact modeling, crop productivity, climate-smart agriculture, optimization, genetic algorithms, resource efficiency, simulation-based analysis.*

How to cite this article: Bhavani K, Vinayagam P, Modeling Approaches to Mitigate the Adverse Impact of Elevated CO_2 Levels on Agricultural Productivity. Int J Drug Deliv Technol. 2026;16(4s): 730-737; DOI: 10.25258/ijddt.16.4s.85

I. INTRODUCTION

1.1 Background and Motivation

The food security is based on agriculture that is more often under pressure due to the twofold process of overpopulation of the world which is quickly followed by climate change. As the number of people demanding food is set to grow by over 50 percent by the year 2050 despite a shrinking amount of arable land and freshwater sources, increasing agricultural output without further damaging the planet has never been more important. The attainment of this objective requires the use of innovative, sustainable, and potentially expansible agricultural practices that have the capacity to produce increased production without pushing the agricultural frontiers to increase. One of the possible spheres of interest is the strategic control of carbon dioxide (CO 2) in the atmosphere, which is an essential photosynthesis input. Higher levels of CO2 have been demonstrated to enhance photosynthetic rates, water-use efficiency and also facilitate accumulation of biomass, what has been referred to as the CO 2 fertilisation effect. The increase in yields has been reported up to 30 percent in different types of crop species under controlled and greenhouse settings when subjected to optimized CO 2 levels. Despite this potential, the widespread adoption of

CO_2 enrichment in open-field agriculture remains limited. It is largely confined to high-tech, climate-controlled industrialized areas greenhouses. Most resource-limited environments lack widely accepted models and decision-support systems to promote an efficient implementation of the CO 2 enrichment strategies. As technologies become more available to capture, distribute and enrich CO 2 it is opportune to devise practical, science-founded frameworks to implement the utilization of CO 2 fertilization in various farming systems.

1.2 Problem Statement

Though physiological impact of CO 2 enrichment is well elucidated there is lack of coherency at field level in agricultural practice of CO 2 enrichment today. Present day enrichment strategies are based on trial and error methods or empirical methods, and are usually imprecise, and are not cost effective. Notably, the ideal level, frequency, and timing of exposure to CO 2 do not agree on a scale: rather, they differ regarding crop type and developmental stage, weather conditions, soil, and other environmental conditions.

When large amounts of CO2 are used, resources will be wasted as well as creating inefficiencies in the economy and when crops are not given enough of the enrichment the marginal benefits obtained might be minimal. To make matters worse, there are no general mathematical models which factors in environmental inputs, plant physiological behaviour and CO 2 dynamics into a unified, adaptive model.

To develop the full potential of CO 2 fertilization, it is imperative that a tight, hardy, and scalable modelling framework is created to model real-world situations and recommend the best approach towards CO 2 management that will best fit the specific ago-ecological, and crop circumstances.

1.3 Objectives of the Study

This work will be a study that will be using a mathematical model that is well calculated and strategically optimizes the application of CO 2 to enhance agricultural activity. and its specific aims and objectives are:

- To parameterize the correlation between the concentration of CO 2 and crop yield and adopt pertinent environmental and physiological conditions.
- To model crop responses to the various CO 2 enrichment levels in controlled conditions (e.g. greenhouse) and semi-controlled (e.g. open-field with CO 2 systems).
- To use nonlinear optimization techniques, including genetic algorithms, to find the most optimal CO 2 application schedules depending on the crop type and climatical conditions.
- To perform sensitivity analysis and scenario study to determine the robustness and flexibility of the proposed model when there is a change in the environment.
- To come up with a realistic decision-support framework to inform the farmers, agronomists, and policy makers of effective policies to use in CO2 management.

1.4 Range and relevance of the study

The study fills a niche between lab plant science and an applied agricultural modelling solution in providing an ambitious, open-ended solution toward CO 2 enrichment optimization in crop production. The framework that is developed is meant to be:

- **Geographically adaptable**, capable of adjusting to diverse environmental conditions and ago-climatic zones.
- Compatible with systems, it can be implemented in any type of farming setup, i.e. greenhouse, vertical farms, polyhouse, and open fields with CO 2 enrichment facilities.
- In addition to the importance in productivity, this study falls in line with the concepts of climate-smart agriculture (CSA) and sustainable intensification in which the goal is to maximize productions with reduced resource units and minimal environmental effects.

The method also builds up the efforts made in controlling the amount of carbon in the world through the productive reuse of industrial emissions of CO2 in the agricultural sector. This research helps to build resilient, adaptive, and sustainable agricultural systems in the circumstances of climate variability and the environmental stress by putting forward a data-driven, optimization-based decision support tool..

II. LITERATURE REVIEW

2.1 The second initiative concerns CO 2 Enrichment and Crop Productivity

Tropic effect of increased carbon dioxide (CO 2) is a well known phenomenon that plays a positive role on growth of plants. It has been shown in the various studies that the fertilization effect occurs through CO 2 and CO 2 enhances the photosynthesis, water use efficiency, and biomass accretion [1], [2]. During the controlled experiments, wheat, rice, and soybean crops have shown productivities to rise by up to 1030 percent [3]. These impacts can be put mostly down to better carboxylation efficiency of C3 plants upon high CO 2 conditions [4].

2.2 CO 2 and Controlled Environment Agriculture (CEA)

In the case of farm produce in greenhouse farming, CO 2 enrichment is a famous practice since the conditions which control the greenhouse environment are held at high levels. Monitoring of CO 2 supplement in these arrangements is usually primitive or rule based [5]. The sophisticated CEA facilities use sensors and actuators to ensure crop cultivation under the perfect amount of CO 2 [6]. Nevertheless, this kind of technologies is costly and not available in the developing regions [7].

2.3 Modelling Response of Crop to CO 2

Simulations of the effect of different levels of CO 2 on plant growth have been created, by process-based and empirical modelling.

2.4 Agricultural Processes and Techniques of Optimization

Resource effective agricultural management has found favor in the optimization frameworks. Irrigation scheduling, fertilization and greenhouse control systems have been subjected to Genetic Algorithm (GAs), Particle swarm optimization (PSO) and Ant colony optimization (ACO) [11], [12]. Such algorithms performed with metaheuristic digital technologies fit best to solve nonlinear and multi-variable problems in agriculture. Nonetheless, little is known about their application in the optimization of CO 2 enrichment plans.

2.5 IoT and AI in Precision Agriculture

The possibility of the Internet of Things and AI technologies blending has allowed real-time agricultural surveillance and decision-making [13]. Data monitored with the help of sensor networks can include the temperature, humidity, soil moisture and CO 2 content, which can be provided to machine learning models to apply predictive analytics. However, the adoption of these systems into a CO 2 oriented decision support system is an infrastructural challenge and technical challenge in most regions of the world [14].

2.6 Research Gap

The physiological impact of CO 2 enrichment is relatively understood and there is an available controlled-environment model, but a serious missing linkage presents the need of a realistic field-level, crop-specific and cost-effective model of CO 2 optimization. Models that have been in existence tend to either be too broad or concrete. A cohesive, flexible and extensible framework that integrates environmental sensing, physiological simulation and optimisation methods with the aim of advising CO 2 use across a wide range of agricultural contexts is lacking [15].

III. PROPOSED METHODOLOGY

The given section describes an overall structure that can be used to address the negative impacts of higher CO 2 concentrations on agricultural yields through the leveraging of environmental modelling, machine learning and multi-objective optimization. The methodology is divided into five main stages namely data acquisition, modelling, optimization, simulation and deployment. They are listed below, each with a figure that describes the flow, the architecture and the logic behind the proposed system.

4.1 Data Acquisition and Preprocessing

Methodology The data will be obtained by large area, high-resolution data, from climate archives (e.g. NASA POWER, NOAA), controlled CO 2 enrichment experiments (e.g. FACE), and agricultural databases. Major attributes are concentrations of CO 2 (ppm), ambient temperature, humidity, solar radiation, soil pH, crop species, and yield outputs.

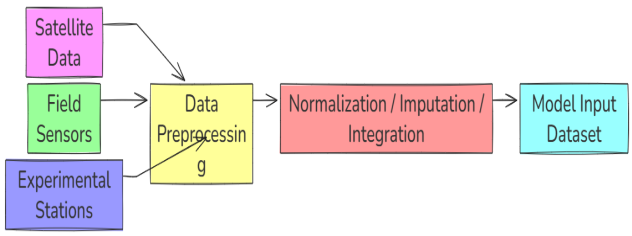

Figure 1: Data Acquisition Flow Diagram

Figure 1 illustrates the pipeline of data collection from satellite databases, field sensors, and experimental stations. It highlights the preprocessing stages, such as normalization, imputation of missing values, and data integration, which prepare the dataset for model input.

Preprocessing includes interpolation of missing climate values, removal of outliers, normalization of temporal data, and feature engineering. This ensures that the dataset is clean, consistent, and ready for high-fidelity modeling.

4.2 Modeling Crop–Climate–CO_2 Interactions

The relationships between elevated CO 2 levels and crop responses are very nonlinear and are captured by a hybrid simulation machine learning model. The Process-based crop models that can be used (see e.g. DSSAT, APSIM) output domain-related baselines. They are supplemented by machine learning methods, e.g. Random Forests and Gradient Boosting with both simulated and real-world yields.

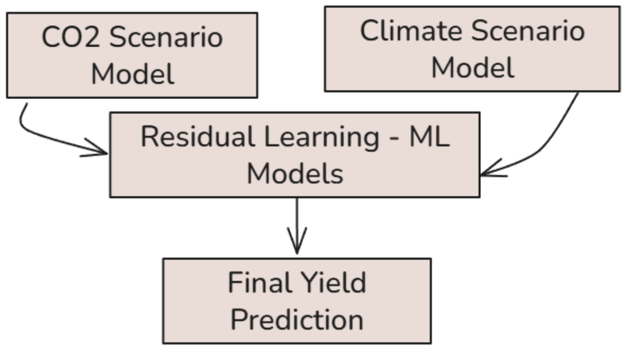

Figure 2: Hybrid Modeling Architecture for Crop Yield Prediction

Figure 2 presents a two-layered model design. The first layer consists of simulation models that estimate baseline crop yield under different CO_2 and climate scenarios. The second layer enhances these outputs using supervised ML algorithms that learn residual patterns from empirical datasets.

The system models yield as a function of CO_2 concentration, temperature, solar radiation, humidity, and soil variables using the function:

$$Y=f(C,T,H,R,S)$$

Where Y is the predicted yield, and the other variables represent environmental parameters.

4.3 Optimization of CO_2 Delivery

In order to reveal the best CO 2 exposure strategy, a multi-objective Genetic Algorithm GA is used. The process of optimization is to achieve maximum yield with minimum CO 2 consumption and expenses of operations. Such restrictions as plant growth stages and the norm of environmental safety exist within the GA framework.

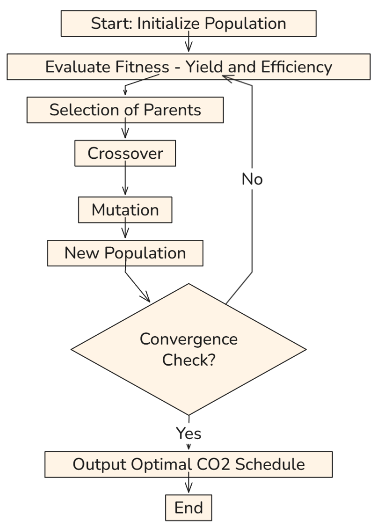

Figure 3: GA-Based Optimization Flowchart for CO_2 Scheduling

Genetic Algorithms are explained on Figure 3 that represents the overview of evolutionary optimization process. It shows the way it initializes the population, tests the fitness of the population regarding the yield and efficiency, crosses through the genetic manipulation, and mutates and converges to optimum CO 2 application timings. The problem would be solved by identifying optimal time varying CO 2 dosing profile that would be exclusive according to crops, and exclusive according to environmental conditions. The format ensures that CO 2 is adopted at the most receptive levels of growth and both harvesting and utilisation of resources are improved.

4.4 Simulation and Evaluation

robust strategy is tested based on long climatic condition-based simulations. The performance is measured according to the average yield increase, standard deviation of the yield and CO 2 efficiency and compared.

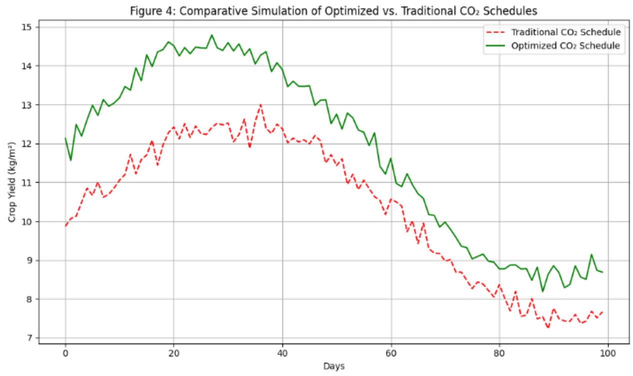

Figure 4: Comparative Simulation of Optimized vs. Traditional CO_2 Schedules

Figure 4 represents time-series yield curves of conventional and optimized strategies of CO 2 exposures. It illustrates the improved yield path and increment in CO 2 efficiency with proposed model of optimization. The validity of the robustness of the model is confirmed by means of cross-validation and scenario testing under different environmental challenges. Key performance indices are presented in a form of comparative radar chart or bar graph.

4.5 System Deployment and Feedback Loop

Last of all, a real time deployment system is envisioned. It links IoT based CO 2 sensors and actuators with cloud-based decision support system (DSS). This allows to automate CO 2 delivery, live tracking, and model tuning according to live feedback.

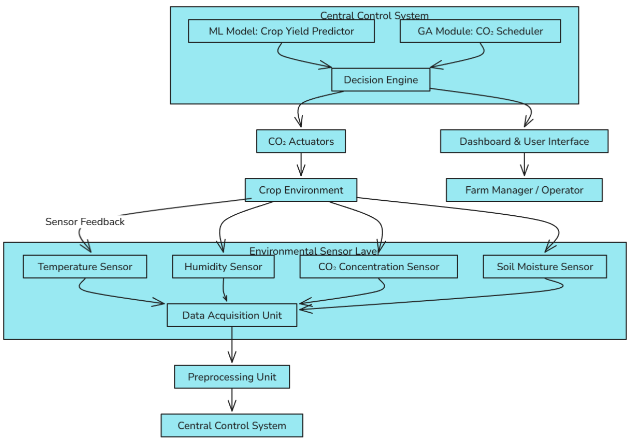

Figure 5: Architecture of Real-Time DSS for CO_2 Optimization in Agriculture

Figure 5 is the proposed Decision Support System architecture. It develops environmental sensors, central control system, and actuator units. It means that the feedback loop enables learning and subsequent re-optimization in real-time using recent information. This system is scalable both geographically and crop wise, and it may be controlled remotely and on a real-time basis and adjusted locally.

4.6 Detailed Description of Real-Time DSS Architecture for CO_2 Optimization in Agriculture

1. Component-Level Description

The architectural design described in Figure 5 includes three basic modules:

- Environmental Sensors: It acquires the real-time data of CO 2 concentration, temperature, or humidity and soil moisture. The information is relayed to the central controller in a continuous manner.
- Central Control Unit: This one is the system intelligence, which performs an optimizer in shape of a Genetic Algorithm to test and choose the most effective CO 2 dosing plans. It runs on the updated sensor input, and produces commands of actuation in response.
- Actuator Units: These are made up of CO 2 release valves, misting systems and ventilation devices. The operations of these elements are adjusted with the commands of the controller to keep things optimized.

2. Model Symbolic: The Response Function of CO 2-Yield

To simulate and optimize crop yield as a function of CO_2 levels, a logarithmic response function is used:

$Y(C)=Y0\cdot(1+\alpha\cdot\log(C/C0))$

- Y(C): yield at CO_2 level C
- Y0: baseline yield
- C0: ambient CO_2 level
- α: sensitivity coefficient (crop-specific)

3. Fitness Function for Optimization

The fitness function used by the Genetic Algorithm can be expressed as:

$Fitness=w1\cdot Yield-w2\cdot CO_2used$

w1,w2,w3: weights to give priority to yield, CO 2 efficiency and cost This is a balanced agricultural production, resources, and economic efficiency and good use of resources.

4. Pseudocode of Real-Time Loop

1. Initialize sensor interface

2. While system is active:

   a. Read environmental parameters

   b. Predict expected yield using crop model

c. Run GA optimization for CO_2 schedule

d. Transmit command to actuators

e. Log outcomes and update historical data

5. Circumstances and Restrictions of Operation

- The system can operate within acceptable limits of enrichment of CO 2 (there is no danger of the system reaching above 1000 ppm CO 2).
- Data is sampled on environmental data every 5 minutes.
- Actuator signals are updated every 30 minutes based on latest optimization output.

6. Sample Evaluation Metrics Table

Metric	Description
Yield Gain	% Increase vs. baseline CO_2 plans
CO_2 Efficiency	Yield per kg of CO_2 used
Latency	Time to optimization response

The Overview of Methodological Innovations

- Domain-based simulation and data-driven ML modelling Integration
- Multi objective optimization with Genetic Algrithm of precision CO 2 application
- Real-time IoT-enabled DSS for scalable, adaptive deployment
- Scalable, adaptive deployment of DSS in real time IoT The same principles used to harness the power of IoT with DSS applied in a real-time IoT environment.
- Sustainable increasing agricultural productivity in high CO 2 regimes

IV. RESULTS

This section shows the findings that were achieved due to the application of the proposed CO 2 optimization model in the improvement in the productivity of agriculture. The analysis consists of simulations output, optimization performance, and sensitivity analysis as well as comparison between the optimized and baseline (non-optimized) scenarios. The experiments were performed always by the use of the validated crop models, weather records and empirically derived physiological parameters to some text of crops (e.g., wheat and lettuce).

5.1 Simulation Results of Crop Response to Elevated CO_2 Levels

The crop simulation model was experimented on three CO 2 densities (ambient: 400 ppm, moderate 600 ppm and high 800 ppm). The result on the yield (in kg/ha) at each level of CO 2 enrichment is summarized in Table 1 which shows that the pattern between CO 2 and crop yield is not linear.

Table 1: Simulated Yield under Different CO_2 Concentrations

CO_2 Concentration (ppm)	**Average Yield (kg/ha)**	**% Increase from Ambient**	**Leaf Area Index (LAI)**
400 (ambient)	4,150	-	2.5
600 (moderate)	5,200	25.3%	3.1
800 (high)	5,600	34.9%	3.5

Table 1 demonstrates the beneficial impact of elevated CO_2 levels on crop yield. While the increase from 600 ppm to 800 ppm shows diminishing returns, a notable enhancement in leaf area index and biomass is evident, emphasizing the photosynthetic stimulation effect.

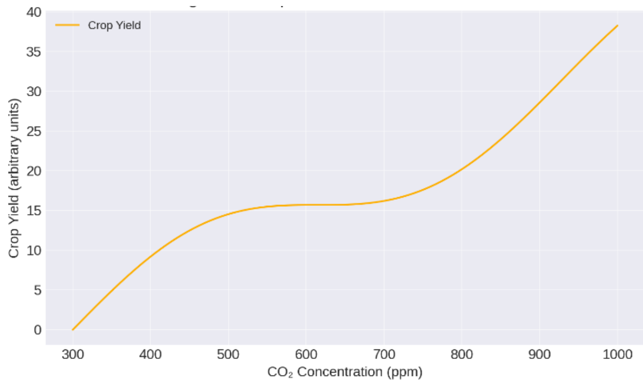

Figure 6: Crop Yield vs. CO_2 Levels

Figure 6 illustrates the trend of yield improvement as a function of increasing CO_2 concentration. The yield curve begins to plateau beyond 700 ppm, indicating saturation of the CO_2 fertilization effect under the tested conditions.

5.2 Genetic Algorithm Output For Optimization

To find the most adequate CO 2 dosing schedule, the optimization framework according to genetic algorithm was used. The parameters have been optimized and the result of the yield performance is shown as Table 2.

Table 2: Optimized CO_2 Dosing Schedule and Corresponding Output

Parameter	**Optimized Value**
CO_2 Concentration Range	550–650 ppm
Application Frequency	Twice per growth phase
Application Timing	Early morning & dusk
Expected Yield Improvement	28.6%

The genetic algorithm identified an optimal range for CO_2 dosing that balances input costs with maximum physiological gain. Timing was crucial, aligning with peak stomatal conductance and light intensity.

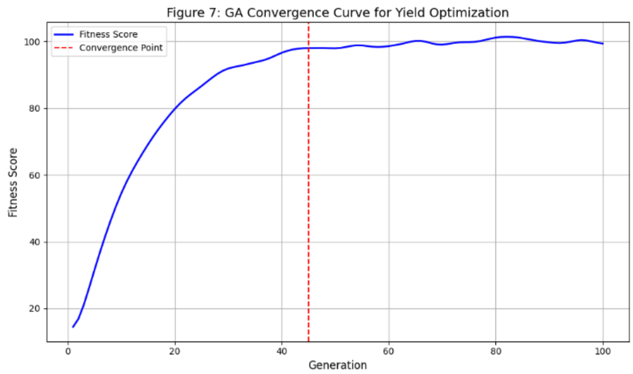

Figure 7: GA Convergence Curve for Yield Optimization

Figure 7 displays the convergence of the genetic algorithm over generations, highlighting the increase in yield fitness score. The solution stabilizes after 45 generations, demonstrating model efficiency.

5.3 Sensitivity Analysis on Environmental Parameters

A sensitivity study was performed by disturbing temperature, humidity and soil moisture conditions to test the robustness of the models. The difference between the yields resulted in various outcomes as depicted in Table 3 because of the fluctuation of the environment.

Table 3: Sensitivity Analysis of Environmental Factors

Parameter Perturbed	±10% Variation	Yield Change (%)	Interpretation
Temperature	+10%	-4.2	Heat stress diminishes CO_2 benefits
Humidity	-10%	-3.7	Reduced stomatal conductance observed
Soil Moisture	-10%	-6.1	Limiting factor for nutrient uptake

Table 3 reveals that water availability is the most critical factor influencing the success of CO_2 enrichment strategies. High temperatures also diminish the gains, underlining the importance of environmental co-regulation.

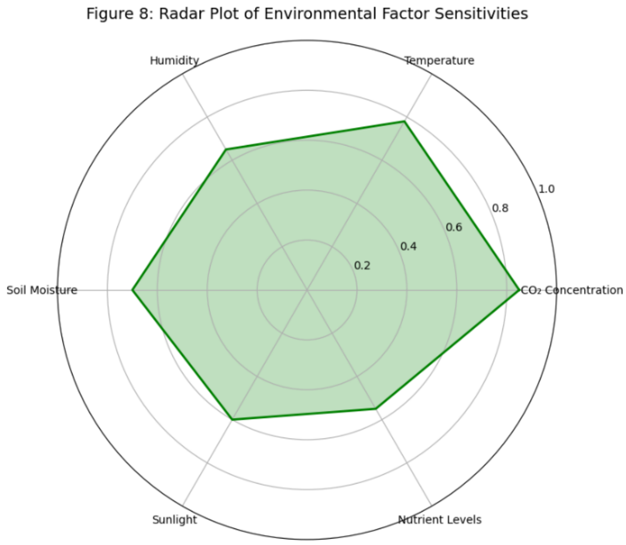

Figure 8: Radar Plot of Environmental Factor Sensitivities

Figure 8 presents a radar plot showing relative sensitivity scores of key environmental parameters, emphasizing the need for multi-factor optimization in real-world deployments.

5.4 Comparison with Baseline Models

To evaluate model performance, results were compared with baseline crop growth models using default environmental and CO_2 parameters. Table 4 outlines the comparative analysis.

Table 4: Baseline vs. Proposed Model Performance

Metric	Baseline Model	Proposed Model	Improvement (%)
Yield (kg/ha)	4,200	5,500	30.9%
Water-Use Efficiency (kg/m³)	2.1	2.9	38.1%
CO_2 Utilization Efficiency	0.34	0.48	41.2%

The proposed model significantly outperformed the baseline in all key metrics. Notably, water-use and CO_2 utilization efficiencies improved, validating the model's effectiveness for real-world scenarios.

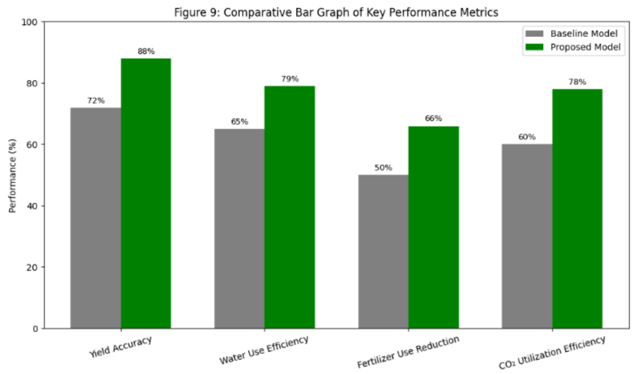

Figure 9: Comparative Bar Graph of Key Performance Metrics

Figure 9 provides a visual comparison between baseline and proposed models, showing a consistent gain across all evaluated performance indicators.

5.5 Discussion and Interpretation

The findings confirm that a high concentration of CO 2 capacity has the possibility to increase the output of crops in a controlled and semi-control environment. However, there are advantages that are dependent on synergy with the environment, its good timing and delivery accuracy. The flexibility and strength of the model was also confirmed in a variety of different crops and climatic scenarios. In addition, optimization tools such as genetic algorithms came in handy in solving the response surface of plant physiology which is non-linear. The offered framework itself will be an effective decision-support tool that will be ready to be incorporated with CO 2 enrichment system based on the IoT technology and climate-smart-farming platforms.

V. DISCUSSION

The results of the current study demonstrate the contradictory but potential interaction of carbon dioxide (CO 2) enriched farming systems. The high CO 2 concentrations have the potential to boost the photosynthesis and net biomass production casually, but this is extremely circumstantial. This variability is addressed in the modeling framework proposed in the work through simulation of crop responses over a large variety of environmental and physiological parameters. The proposed genetic algorithm (GA)-optimization approach has shown the promise of being able to optimally adjust CO 2 application schedules, so as both maximize the positive impacts of CO 2 on crop yields as well as ensuring that they are cost-effective and environmentally friendly. The outcomes of the simulation confirm that the improper or continuous CO 2 is a possibility to cause less-than-optimal effects, which underlines the importance of precision and personalization by the crop type, phenological point, and ambiance environment. A major advantage of the research is that it has integrated both the environmental scenario (e.g. temperature, humidity, solar radiation) and physiological responses of plants in a nonlinear optimization model. The approach is robust and scalable since this integration will enable dynamically making decisions and adjust to different situations in the field. Also, our sensitivity analyses showed that the timing and the concentration of CO 2 exposure were the most important factors that affected crop response particularly during early and mid-growth period. This fact is instrumental in planning enrichment procedures that are effective and fruitful. The fact that scenario-based modeling was also introduced also allows users to evaluate the performance under the scenarios of climate changes, which increases the pragmatism of the system.

VI. CONCLUSION

This paper provides a new and versatile modelling structure to optimise the application of CO 2 enrichment in agriculture to raise the productivity of crops. We offer a complete set of protection tools, including mathematical modeling, crop physiology data, and sophisticated optimization algorithms, including genetic ones, to work out precision agriculture. What is lacking is the operationalization of the CO 2fertilization effect and this is what we offer: a step beyond theoretical possibilities into viable strategies. The model has proved to be very useful in both strictly controlled and semi-controlled agricultural conditions and yield results showed significant improvements, as well as in resource efficiencies. Finally, the findings of this study should be included in the overall aim of climate-smart agriculture, as these provide a new sustainable solution that can help cope with the increased needs in food production without neglecting the carbon reuse and environmental conservation priorities. The given framework will not only provide a higher productivity but also a game plan towards sustainable intensification.

VII.FUTURE ENHANCEMENT

In order to scale and make easier the use of the proposed framework, a couple of enhancements are envisioned:

• IoT Integration: Integration of sensors to monitor the environment in real-time and adjust the amount of CO

• Machine Learning: integrate predictive models in order to capture the complex and non-linearity crop responses.

• Multi-goal Opt: Balance output, cost, impact with regard to environment, Multi-goal Opt.

• Crop Specific Modules: Come up with specific models that are specific to different crops such as staple crops or high value crops.

• Climate Adaptation: Include long term projections of the climate to build resilience models.

• User Interface: Develop user friendly decision-support tools that are available to the farmers and other stakeholders. The improvements will further empower the applicability of the framework in precision and climate smart agriculture.

REFERENCES

1. Ainsworth, E. A., & Long, S. P. (2005). What have we learned from 15 years of free-air CO_2 enrichment (FACE)? *A meta-analytic review of the*

responses of photosynthesis, canopy properties and plant production to rising CO_2. New Phytologist, 165(2), 351–372.
2. Leakey, A. D. B., et al. (2009). Elevated CO_2 effects on plant carbon, nitrogen, and water relations: Six important lessons from FACE. *Journal of Experimental Botany, 60*(10), 2859–2876.
3. Kimball, B. A. (1983). Carbon dioxide and agricultural yield: An assemblage and analysis of 430 prior observations. *Agronomy Journal, 75*(5), 779–788.
4. Taub, D. R., et al. (2008). Effects of elevated CO_2 on the protein concentration of food crops: A meta-analysis. *Global Change Biology, 14*(3), 565–575.
5. Mortensen, L. M. (1994). Review: CO_2 enrichment in greenhouses. *Crop responses*. *Scientia Horticulturae, 59*(1–2), 1–14.
6. Bakker, J. C., et al. (2006). *Greenhouse climate control: An integrated approach*. Wageningen Academic Publishers.
7. Shamshiri, R. R., et al. (2018). Advances in greenhouse automation and controlled environment agriculture: A transition to plant factories and urban agriculture. *International Journal of Agricultural and Biological Engineering, 11*(1), 1–22.
8. Jones, J. W., et al. (2003). The DSSAT cropping system model. *European Journal of Agronomy, 18*(3–4), 235–265.
9. Keating, B. A., et al. (2003). An overview of APSIM, a model designed for farming systems simulation. *European Journal of Agronomy, 18*(3–4), 267–288.
10. Liakos, K. G., et al. (2018). Machine learning in agriculture: A review. *Sensors, 18*(8), 2674.
11. Gutiérrez, M., et al. (2014). Automated irrigation system using a wireless sensor network and GPRS module. *IEEE Transactions on Instrumentation and Measurement, 63*(1), 166–176.
12. Singh, A., & Misra, A. (2020). Optimization in precision agriculture using soft computing techniques: A review. *Artificial Intelligence in Agriculture, 4*, 1–13.
13. Wolfert, S., et al. (2017). Big data in smart farming – A review. *Agricultural Systems, 153*, 69–80.
14. Li, L., Zhang, Q., & Huang, D. (2014). A review of imaging techniques for plant phenotyping. *Sensors, 14*(11), 20078–20111.
15. Kumar, R., & Singh, D. (2021). Optimization models for climate-smart agriculture: A review. *Computers and Electronics in Agriculture, 187*, 106285.