Hydroponic Crop Cultivation (HCC) for Global Food Security

A

Dissertation

Presented to

the faculty of the School of Engineering and Applied Science

University of Virginia

in partial fulfillment

of the requirements for the degree

Doctor of Philosophy

by

Boyang Lu

May 2025

APPROVAL SHEET

This

Dissertation

is submitted in partial fulfillment of the requirements
for the degree of

Doctor of Philosophy

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Abstract

Food security is an urgent global challenge, particularly in Small Island Developing States (SIDS), where traditional agriculture is highly vulnerable to climate change and extreme weather events. Hurricanes and tropical storms frequently disrupt food production, infrastructure, and supply chains, exacerbating the reliance on food imports and increasing economic instability. To address these challenges, this dissertation investigates Hydroponic Crop Cultivation (HCC) as a climate-resilient agricultural alternative to Conventional Crop Cultivation (CCC).

The research begins with an experimental analysis of HCC and CCC in Chapter 2, evaluating yield performance, water-use efficiency, and climate adaptability. Results indicate that HCC achieves up to 6.4 times higher yield per growth cycle than CCC, shortens growth cycles by up to 60%, and improves water-use efficiency by a factor of eight, making it a promising solution for sustainable agriculture in SIDS. Additionally, two hydroponic system designs—tray-based and Dutch bucket systems—were developed and tested, demonstrating scalability and adaptability to different environmental conditions.

Building on these findings, Chapter 3 addresses operational optimization by developing a stochastic optimization model for HCC production planning under demand uncertainty. Given the unpredictable nature of energy supply, food demand, and hurricane disruptions, the model optimally balances crop production, energy use, and inventory management, ensuring that HCC remains economically viable and operationally resilient. The results show that risk-aware decision-making frameworks significantly reduce operational costs while stabilizing food production, reinforcing the feasibility of large-scale HCC implementation.

While Chapter 3 focuses on production efficiency, Chapter 4 evaluates the resilience of HCC in mitigating food shortages and economic losses caused by hurricanes using system dynamics modeling. The analysis demonstrates that higher adoption rates of HCC significantly reduce post-hurricane food insecurity and accelerate agricultural recovery. The study also identifies key feedback loops between hydroponic adoption, government policy interventions, and disaster response strategies, providing a data-driven approach for integrating HCC into climate adaptation planning.

Finally, Chapter 5 shifts toward strategic agricultural planning, developing a portfolio optimization model that guides farmers and policymakers in crop selection, resource allocation, and investment decisions under climate risk. The model demonstrates that a diversified hydroponic farming strategy can increase net economic returns while reducing agricultural risk, offering a scalable framework for long-term climate-resilient food security strategies.

The dissertation's findings contribute to multiple research domains, including agricultural resilience, climate adaptation, and sustainable food systems, by demonstrating that HCC is not only technically viable but also operationally sustainable and economically scalable. By integrating empirical evidence with advanced modeling techniques, this research provides

scientific, policy, and practical insights for transitioning toward climate-resilient agriculture in SIDS and other regions facing similar environmental challenges.

Acknowledgment

The completion of this dissertation marks the culmination of years of research, learning, and personal growth, and I am deeply grateful to those who have supported me throughout this journey.

First and foremost, I would like to express my deepest gratitude to my advisor, Dr. Garrick Louis, for his unwavering guidance, patience, and encouragement. His mentorship has been instrumental in shaping my academic and professional trajectory. His insightful feedback, rigorous approach to research, and steadfast support have not only helped me navigate the complexities of my dissertation but have also inspired me to push the boundaries of knowledge and impact-driven scholarship.

I am also profoundly grateful to my dissertation committee members, Dr. James H. Lambert, Dr. Michael C. Smith, Dr. Henning S. Mortveit, Dr. Leonard Githinji, and Dr. Manuel T. Lerdau. Their invaluable feedback, constructive critiques, and intellectual generosity have greatly enriched my work. Their diverse expertise and perspectives have challenged me to think critically and refine my research, ensuring that it contributes meaningfully to both theory and practice.

Beyond academia, I owe my deepest appreciation to my parents, whose unwavering support and unconditional love have been the foundation of my journey. Their sacrifices, encouragement, and belief in my potential have sustained me through the challenges of this academic pursuit. Their resilience and dedication serve as my greatest inspiration, and I am forever grateful for their presence in my life.

Finally, I would like to thank my colleagues, friends, and everyone who has contributed to my academic and personal growth. Whether through insightful discussions, collaborative projects, or simply words of encouragement, each of you has played a role in shaping my path.

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Chapter 1

Introduction

As global food security challenges intensify due to climate change, there is an urgent need for innovative agricultural solutions that can withstand environmental shocks while ensuring sustainable food production. Traditional soil-based farming methods, particularly in vulnerable regions such as Small Island Developing States (SIDS), are increasingly threatened by extreme weather events, water scarcity, and land degradation. This dissertation investigates Hydroponic Crop Cultivation (HCC) as a transformative approach to building climate-resilient food systems. By integrating experimental research, system dynamics modeling, and optimization techniques, this study seeks to bridge the gap between theoretical advancements in hydroponic technology and their practical implementation in food-insecure regions. The following sections outline the motivation behind this research, the specific objectives of the study, and the methodological approach used to assess the feasibility, scalability, and policy implications of HCC.

1.1 Motivation and Background

Food security remains one of the most pressing global challenges in the 21st century, particularly as climate change intensifies its impact on traditional agricultural systems. Small Island Developing States (SIDS) are among the most vulnerable regions to climate change, with their agricultural sectors facing severe threats from rising sea levels, saltwater intrusion, land degradation, and an increasing frequency of extreme weather events, particularly hurricanes. These nations, which include the Caribbean, Pacific, and Indian Ocean islands, depend heavily on imported food due to the limited availability of arable land, further exacerbating their vulnerability to global food supply disruptions and price volatility.

According to the United Nations, over 50% of the food consumed in SIDS is imported, and in some cases, this figure reaches as high as 80% (United Nations, 2021). The dependence on external food supplies makes these regions highly susceptible to international market fluctuations, supply chain disruptions, and climate-induced disasters. When hurricanes strike, they can not only devastate local food production but also disrupt transportation and logistics, delaying the importation of essential food supplies. The 2017 hurricane season, for instance, saw Hurricane Maria inflict damages amounting to over 225% of Dominica's GDP, causing widespread food shortages and economic instability (Baptiste et al., 2020).

The vulnerability of conventional crop cultivation (CCC) in SIDS is particularly evident in the aftermath of such disasters. Traditional agriculture in these regions relies on open-field cultivation, which is directly exposed to extreme weather. High winds, torrential rainfall, and flooding can destroy crops, erode topsoil, and contaminate freshwater resources with saltwater, rendering fields unusable for multiple seasons. Even in non-hurricane periods, unpredictable rainfall patterns and prolonged droughts post a challenge to food production. These environmental stressors necessitate the exploration of innovative, resilient agricultural solutions that can operate effectively within the unique constraints of SIDS.

Hydroponic Crop Cultivation (HCC) presents a viable alternative to CCC, offering a controlled environment for food production that is less dependent on arable land and more resilient to climate-induced disturbances. Unlike traditional farming, hydroponic systems involve the growing of crops in soilless media such as nutrient-rich water solutions, eliminating the need for soil and allowing for precise control over nutrient delivery, water use, and growing conditions. This method significantly reduces water consumption—an essential factor for SIDS, where freshwater resources are limited and increasingly threatened by saltwater intrusion.

Several key advantages of HCC make it particularly suitable for SIDS:

1. **Climate Resilience:** Hydroponic systems can be housed in protected environments such as greenhouses, vertical farms, or floating structures, reducing exposure to hurricanes, heavy rainfall, and extreme temperatures. These systems can also be designed with storm-resistant features, allowing them to be dismantled or relocated in the event of a severe weather event.

2. **Water Efficiency:** Traditional farming in SIDS faces critical challenges related to water availability and quality. HCC uses up to 90% less water than soil-based farming by recycling water within a closed-loop system, making it ideal for regions where freshwater is scarce or at risk of contamination (Savvas, 2003).

3. **High Yield and Space Efficiency:** Given the limited arable land in SIDS, maximizing food production per unit area is essential. Hydroponic systems can be vertically stacked or installed in urban environments, increasing food production density without requiring extensive land conversion. HCC also accelerates crop growth cycles, allowing for multiple harvests per year compared to conventional methods.

4. **Energy Adaptability:** One of the main challenges in SIDS is the high cost and instability of energy supplies, which are often reliant on imported fossil fuels. However, HCC can be integrated with renewable energy sources such as solar microgrids, enabling off-grid operation and further enhancing resilience.

Despite these advantages, there is still limited empirical research on its scalability, long-term economic viability, and social acceptance among local farmers.

1.2 Dissertation Structure

This dissertation seeks to explore the role of Hydroponic Crop Cultivation (HCC) in enhancing agricultural resilience, particularly in Small Island Developing States (SIDS) that face food security challenges due to extreme weather events like hurricanes. By integrating empirical experimentation, system dynamics modeling, and optimization techniques, this research develops a holistic framework for understanding how HCC can complement traditional agriculture, improve food security, and support climate adaptation policies. This research was funded by an UVA 3 Cavaliers grant from 2018 to 2019 and NSF EAGER grant from 2020 to 2022.

This dissertation is structured into six chapters. Chapter 1 provides an overview of the research rationale, goals, objectives, and methodology, outlining the significance of HCC in addressing food security challenges. Details for Chapters 2, 3, 4 and 5 has been shown in Table 1. Chapter 6 synthesizes the key findings and contributions, directions for future research, career forward and publications.

Table 1. Research goals, objectives, activity/methods, and associated chapters

Research Goals		Research Objectives	Activity/Methods	Chapter
1	To develop off-grid, rainwater-based HCC systems to compete with CCC in reducing the risk of food insecurity in SIDS.	• Design, build, & test HCC systems appropriate to mitigate hurricane risk to food security in SIDS. • Evaluate the Comparative Performance of the HCC systems to CCC.	• Microgrid-supported hydroponic crop cultivation systems (MSHCC) (Lu & Louis, 2020; Gerlach et al., 2023) • System design	Chapter 2
2	To optimize HCC food production under uncertainty.	• Identify Key Risk Factors in Hydroponic Food Production • Develop a Stochastic Optimization Model for Production-Inventory Planning	• Stochastic optimization • Risk identification • Production-inventory modeling (Lu & Louis, 2021)	Chapter 3
3	To assess the Role of HCC in Enhancing Agricultural Resilience to Hurricanes.	• Simulate the Impact of HCC Adoption on Agricultural Resilience in Hurricane-Prone Regions • Assess the Policy and Optimization Strategies for HCC allocation in Hurricane-Prone Regions.	• System dynamics modeling • Sensitivity analysis • Policy analysis (Lu et al., 2025)	Chapter 4

4	To Develop a Resilient Agricultural Planning Model for SIDS	• Design a Climate-Responsive Agricultural Portfolio Model for SIDS. • Optimize Farming Resource Allocation for Climate-Resilient Agriculture.	• Portfolio modeling • Optimization (Lu & Louis, 2024)	Chapter 5

Goal 1: To develop off-grid, rainwater-based HCC systems to compete with CCC in reducing the risk of food insecurity in SIDS. (Chapter 2)

The first goal is to provide empirical evidence on the viability of HCC as an alternative to CCC by evaluating its performance, including resource efficiency and structural resilience. This goal lays the foundation for understanding how hydroponic systems function in SIDS and informs subsequent modeling and policy discussions.

Objectives:

1. Design, build, & test HCC systems appropriate to mitigate hurricane risk to food security in SIDS.
    - Develop two types of HCC systems (tray-based and Dutch bucket) optimized for resource efficiency and storm resilience.
    - Incorporate renewable energy solutions (solar microgrids) and rainwater collection into the system design.
2. Evaluate the Comparative Performance of the HCC systems to CCC.
    - Conduct a controlled experimental analysis comparing the yield, growth cycle duration, and water-use efficiency of HCC and CCC.

Goal 2: To optimize HCC food production under uncertainty. (Chapter 3)

While Chapter 2 establishes HCC's technical feasibility, Chapter 3 addresses a critical challenge: How can HCC production be optimized in the face of uncertainty? This goal focuses on managing risks in hydroponic production-inventory systems, particularly those arising from fluctuating energy supply, unpredictable food demand, and post-disaster disruptions.

Objectives:

1. Identify Key Risk Factors in Hydroponic Food Production.
    - Use Integrated Definition (IDEF) risk modeling to analyze uncertainties in power supply, demand fluctuations, and inventory risks.

- Determine how HCC production is affected by unpredictable weather events and market conditions.

2. Develop a Stochastic Optimization Model for Production-Inventory Planning.
   - Formulate a multi-period production-inventory model that accounts for fluctuating energy costs and uncertain food demand.
   - Optimize production quantity, inventory levels, and energy consumption to minimize operational costs while ensuring stable food supply.

Goal 3: To assess the Role of Hydroponic Crop Cultivation (HCC) in Enhancing Agricultural Resilience to Hurricanes (Chapter 4)

While Chapters 2 and 3 establish HCC's technical feasibility and operational stability, the next critical question is: How can HCC contribute to agricultural resilience in hurricane-prone regions? This chapter develops a system dynamics model to analyze how HCC adoption impacts food security, farmer income, and market stability during extreme weather events.

Objectives:

1. Simulate the Impact of HCC Adoption on Agricultural Resilience in Hurricane-Prone Regions.
   - Develop a system dynamics model that integrates key variables such as HCC production capacity, hurricane intensity, market demand, and supply chain disruptions.
   - Examine how HCC adoption can mitigate food deficits and stabilize economic conditions in the aftermath of hurricanes.
2. Assess the Policy and Optimization Strategies for HCC allocation in Hurricane-Prone Regions.
   - Develop an optimization model for equitable and cost-effective allocation of HCC units, given budgetary constraints.

Goal 4: To Develop a Resilient Agricultural Planning Model for SIDS (Chapter 5)

Given the complexities of climate change and resource constraints, a data-driven agricultural planning model is needed to guide farmers in selecting optimal crop portfolios and resource allocations. This chapter proposes a regional portfolio model to help farmers make informed decisions under varying climate and resource conditions.

Objectives:

1. Design a Climate-Responsive Agricultural Portfolio Model for SIDS.
   - Develop a data-driven model that accounts for microclimatic variation and resource availability.
   - Evaluate how different crop choices and farming subunits interact to maximize resilience and profitability.
2. Optimize Farming Resource Allocation for Climate-Resilient Agriculture.
   - Assess trade-offs between financial returns and agricultural production risks.
   - Provide policy recommendations to improve agricultural sustainability and regional food security.

1.3 Theoretical and Methodological Contributions

This dissertation makes its most significant contribution through the novel application of systems engineering methodologies to the complex, interdisciplinary challenge of food security, particularly in the context of Small Island Developing States (SIDS). Historically, systems engineering has been extensively applied to domains such as aerospace, information systems, and industrial operations. However, its adoption within sustainable development challenges—especially those related to agricultural resilience and climate adaptation—has been limited.

By integrating stochastic optimization, system dynamics modeling, and resilience engineering principles into the design and evaluation of hydroponic crop cultivation (HCC) systems, this research demonstrates how systems engineering can be systematically extended to model, analyze, and improve socio-technical systems in the agricultural sector. This methodological innovation provides a structured approach to quantifying risks, designing adaptive interventions, and guiding policy under uncertainty—tools that are urgently needed in food-insecure regions experiencing the compounding effects of climate variability and land scarcity.

The work extends the philosophical and methodological boundaries of systems engineering in several keyways. First, it shifts the focus from deterministic optimization toward adaptive and probabilistic system design, acknowledging the high variability and uncertainty present in agricultural systems. Using stochastic models and scenario-based analysis, the research captures the range of possible disruptions (e.g., hurricanes, market volatility) and evaluates system performance under diverse conditions.

Second, the research contributes to resilience engineering theory by showing that resilience in food systems is not only a matter of robustness or recovery, but also of adaptive capacity built into the physical and operational architecture. The HCC system exemplifies a resilient design through its modularity, independence from soil, closed-loop water use, and potential for integration with renewable energy microgrids—all key traits that support sustained functionality during environmental shocks.

Third, this work reflects the interdisciplinary potential of systems engineering when applied to domains traditionally outside its scope. The fusion of engineering methods with agricultural science, environmental systems, and public policy exemplifies a systems-level approach that bridges technical and societal challenges. The research reframes food insecurity as a systems problem, one that requires tools capable of capturing feedback dynamics, uncertainty, resource constraints, and the trade-offs inherent in policy decisions.

Finally, the dissertation highlights the role of systems engineering in supporting ethical and sustainable development. In applying systems methods to vulnerable and underserved regions, the research elevates issues of equity, accessibility, and long-term viability, further demonstrating that the discipline can play a central role in achieving the goals of resilience and food justice in a changing world.

Together, these theoretical insights and practical applications showcase how systems engineering can meaningfully contribute to the design and evaluation of agricultural resilience strategies. This work establishes a replicable methodological foundation for future interdisciplinary research and practical interventions targeting food security under conditions of deep uncertainty.

Chapter 2

Design, Implementation, and Comparative Analysis of Hydroponic Crop Cultivation Systems

A Floating Farm for Hydroponic Crop Cultivation in Small Island Developing States

Published in 2023 Systems and Information Engineering Design Symposium (SIEDS)

Ethan A. Gerlach, Arthur Hoang, Saffiata Kamara, Anwar Longi, Derek A. Sprincis, Ethan W. Thurmond, **Boyang Lu**, and Garrick E. Louis

A Literature Review of Hydroponic Crop Cultivation Research.

Published in Proceedings of the 5th Global Food Security, Food Safety and Sustainability.

Boyang Lu, Garrick E. Louis

Abstract

Hydroponic Crop Cultivation (HCC) has emerged as a promising alternative to Conventional Crop Cultivation (CCC), offering enhanced resource efficiency, accelerated crop cycles, and increased resilience to environmental constraints. This chapter provides a technical analysis of the tray and Dutch bucket system designs, detailing their modular configuration, closed-loop nutrient delivery, and integration of renewable energy sources. A controlled experiment was conducted to assess the yield performance, growth cycle duration, and water consumption efficiency of each system under identical cultivation conditions. The experimental results demonstrate that HCC significantly outperforms CCC, achieving 6.4 times higher yield per cycle, completing growth cycles in 39–55 days compared to 99 days for CCC, and exhibiting water-use efficiency up to 8 times greater than CCC. These findings underscore the capacity of HCC systems to enhance agricultural productivity while minimizing resource consumption, making them particularly suitable for deployment in regions affected by water scarcity and climate variability.

Keywords: Hydroponic Crop Cultivation (HCC), Tray System, Dutch Bucket System, Sustainable Agriculture, Water-Use Efficiency.

2.1 Introduction

Worldwide, some of the most at-risk regions for food insecurity are coastal communities and Small Island Developing States (SIDS) (includes nations in the Caribbean, Pacific, and Indian Oceans) due to a variety of natural and economic factors. Making up approximately 1% of the global population (United Nations, 2020), SIDS face unique challenges due to their small land area, remote geography, and susceptibility to extreme climate events. Current food systems in place face mounting pressures from population growth, availability of fertile soil as well as an increasing rate of extreme weather. According to the UN, climate change is projected to negatively impact the four pillars of food security – availability, access, utilization, and stability – during the 21st century (United Nations, 2022). The economy of Caribbean nations is heavily reliant on agriculture, with significant contributions to their Gross Domestic Products ranging from 7% to 17%. However, despite their capacity for agricultural production, most countries in the region are highly dependent on imported food. In fact, the proportion of food consumed in the region that is imported has risen from 40% to 60% since 1990, with over half of the countries importing more than 80% of their food. This increased reliance on imports, combined with the growing frequency of natural disasters caused by climate change, creates market volatility and food insecurity in the region.

Climate change is exacerbating the current stresses on these pillars through increasing temperatures, changing precipitation patterns, and the increase in frequency, duration, and intensity of extreme weather events like floods, droughts, and hurricanes. According to the University of the Bahamas, global mean sea-level is currently rising at a rate around 3.6 mm per year (Borland et al., 2018). This rate only increases with higher emission scenarios with possible meters of sea level rise by 2300. This is detrimental for the future of coastal communities that support tourism, fisheries, and agriculture industries in the region. SIDS are also vulnerable to extreme weather events which have been exacerbated by the changing climate. These weather events can result in damage at a nationally significant scale since Caribbean SIDS have small economies, areas, and populations. In 2017, Hurricane Maria caused damages that amounted to more than 225% more than the annual GDP of Dominica (Baptiste & Martyr-Koller, 2020). While the effects of climate change will affect every nation, region, and economy of the world, Caribbean SIDS are especially vulnerable due to their close connection to coastal environments.

The Caribbean region has a long history of small-scale farming and food production, with many rural households having a deep connection to the land and a tradition of cultivating their own crops. These farmers often utilize traditional techniques that have been passed down through generations (Natural Water Retention Measures, 2015), such as intercropping, which involves planting multiple crops together in close proximity to maximize yield and use resources more efficiently. This method has numerous benefits, such as reducing soil erosion, filtering pollutants from the soil, and slowing down runoff (Triantaphyllou & Mann, 1955), which helps to maintain the health of local ecosystems. While some small-scale farmers in the Caribbean have adopted more modern methods of farming, such as greenhouse technology and organic farming, many still rely on agri-chemicals like fertilizers and pesticides to increase the productivity of their crops. However, the use of these chemicals can have negative impacts on the environment, including soil and water pollution and harm to beneficial insects and wildlife. Agriculture is a vital sector of the Caribbean economy, with many countries in the region having large agricultural industries that contribute significantly to their GDP. However, despite this, most nations in the region are heavily reliant on food imports, with many importing over 80% of their food. This trend has been increasing since 1990, leading to greater market volatility and food insecurity in the region (Natural Water Retention Measures, 2015). This dependence on imported food also leaves the Caribbean vulnerable to supply chain disruptions and price spikes, which can have devastating impacts on the region's food security.

Despite the challenges faced by small-scale farmers in the Caribbean, there are opportunities for the development of sustainable and resilient food systems in the region. This could include the establishment of cooperative networks and other forms of support for small-scale farmers, as well as increased investment in agricultural research and development to promote more sustainable and efficient farming practices. By prioritizing the development of local food systems and reducing dependence on imports, the Caribbean region can build a more secure and resilient food system that benefits both farmers and consumers alike.

This chapter explores the design, implementation, and comparative evaluation of Hydroponic Crop Cultivation (HCC) systems, including the tray system and Dutch bucket system, in contrast to Conventional Crop Cultivation (CCC). The chapter details the structural design, material selection, and operational mechanisms of both hydroponic systems, emphasizing their suitability for resource-efficient and climate-resilient agriculture. Additionally, a controlled comparative experiment was conducted to assess the performance of HCC and CCC in terms of yield, growth cycle duration, and water consumption efficiency. The results demonstrate the superior productivity and sustainability of HCC, highlighting its higher yield efficiency, shorter growth cycles, and reduced water consumption compared to CCC.

2.2 Methodology

2.2.1 Tray system for leaf crops

Our first HCC design is a tray system, which has been constructed by March 2021. The structure is designed with storm-resistance as the top priority. After speaking to contacts in the Bahamas, it became clear that the best way to protect plants would be to design a structure that would allow the user to bring the plants indoors during a storm. Therefore, the design focuses on collapsibility and transportability.

- **System Design**

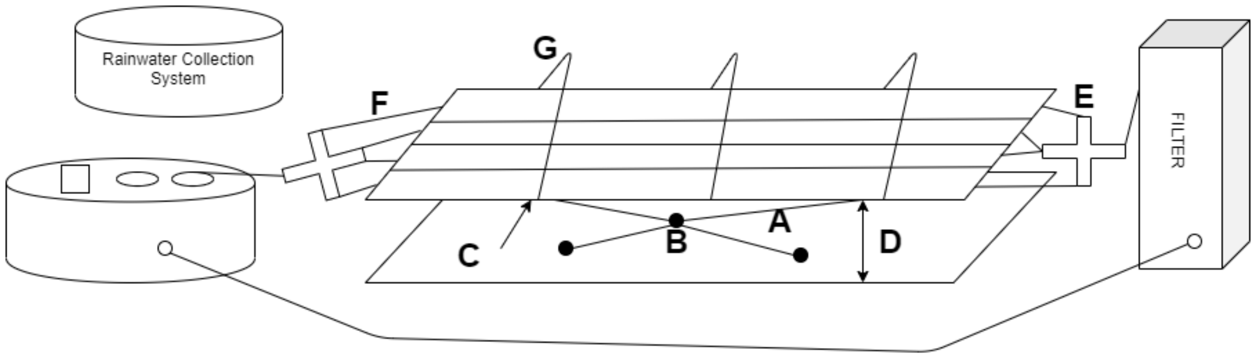

Figure 1. Side view of tray system

The standing structure is 3-feet tall, 4-feet wide, and 5- feet long. There are two separable components in the design that are held together by four clamps: the plant growth unit and the support structure. The user is able to quickly remove these clamps (Fig. 1.C) and carry the plant growth unit inside to a safe location. Moreover, when the clamps are removed, the x-shaped legs (Fig 1.A) collapse at the connector point (Fig 1.B). This allows the legs to be fully removed and the top board to be laid flat on the bottom board (Fig. 1.D). The unit is thus lowered to create a compact base that can be easily brought inside. The junction pieces that distribute and collect water (Fig. 1.E, 1.F) are disconnected as well. Once the storm is over, the user can bring the unit back outside and easily reassemble it to immediately continue farming. In order to address other farming problems, including strong winds and pest intrusion, an agricultural fabric will be installed as a shelter for the plants. Three metal hoops (Fig. 1.G) will be secured around the PVC pipes and plants, providing a protected area for the plants to grow. The pest control fabric will be tightly wrapped around the metal rings, acting similarly to a greenhouse. The fabric will still allow air to flow throughout the system but will partially protect the plants from pests. The fabric will also reduce the amount of rainwater entering the system. This is an important aspect as hydroponic farming is focused on providing plants with the optimal quantity of specific nutrients and water.

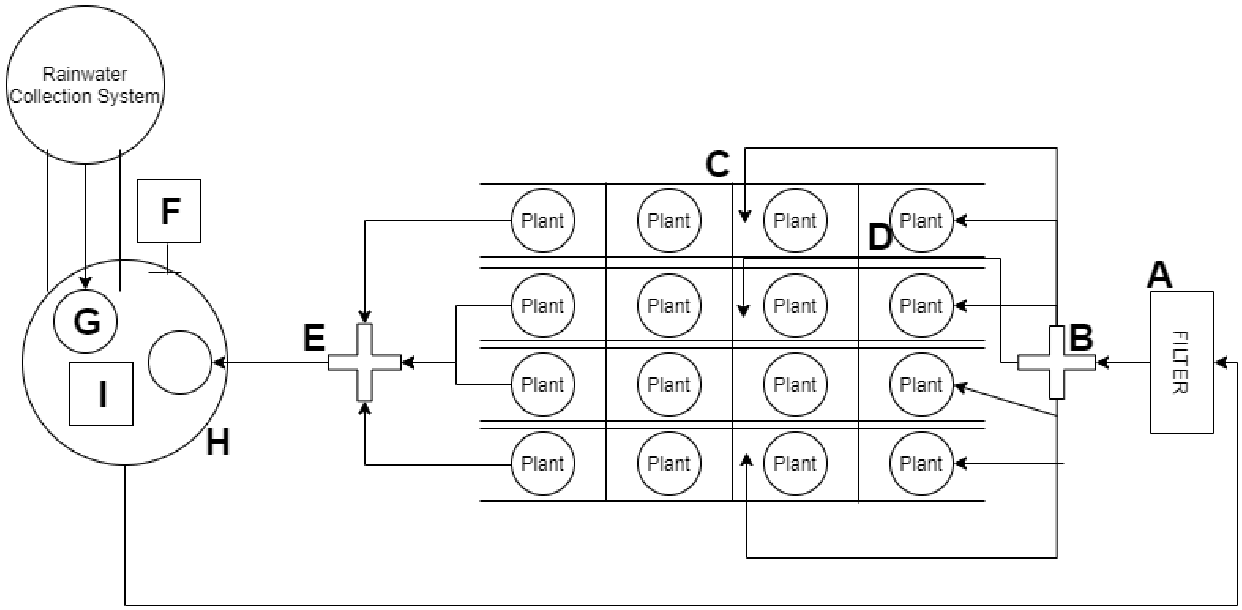

Figure 2. Top view of tray system

The unit is also designed to maximize crop yield. By creating four channels (Fig. 2.B) from filtered water (Fig 2.A), the nutrients are spread out more evenly among the plants, thus improving on the previous design. Once the water flows through the filter and into the PVC pipe channels, the nutrient enriched water will flow through each plant's roots (Fig. 2.C, 2.D) to the end of the base unit. Similarly to the junction connected to the filter, the excess nutrient water will be collected at the bottom of the pipes (Fig. 2.E) and dispersed back into the barrel. If there is insufficient water supply, the "Rainwater Collection System" can also be used to fill up the tank (Fig. 2.G). Finally, water is pumped back to the filter utilizing a solar-powered pump (Fig. 2.H) that lies inside the system. The power for the system comes from the auxiliary solar panel that can input the energy into the system at top of the barrel (Fig. 2.I). Using the controller (Fig. 2.F), the hydroponic user can decide how to distribute the solar energy collected. With the water pumped back into the filter, the process repeats itself.

- **Abundant Water Supply**

The water supply for the unit can come from a variety of sources. In normal conditions, the user can fill the nutrient barrel with water from their house connection, a well, or another water source. If there is a disruption to the site, such as a pollutant or pathogen in the water supply, or saltwater intrusion, the user can connect the nutrient barrel to a rainwater collection system and use rainwater to water their plants. It is important that the water supply is clean in order to produce safe, healthy crops. In addition, there is a slow sediment filter that can filter out harmful particles in order to make the water potable in an emergency situation. This enhances the quality of the water not only for the plants, but also for humans if they need an emergency water supply.

- **Utilizing Solar Power**

During the hurricane season in SIDS, the grid power system can be unreliable and is susceptible to frequent power outages. After large storms, the typical grid power system on these islands can be out for months at a time, leaving the locals to resort to alternative energy sources. For our unit we looked into solar, wind, and gas as potential power sources. After evaluating different energy options, we ruled out wind due to scalability challenges and gas due to cost and dependency issues, ultimately selecting solar power as the most suitable alternative. With many SIDS farmers already making the switch to solar, it was clear that this type of renewable energy would work well in this environment and allow for the unit to be removed from the unstable island power grid. Moving forward with solar energy, we determined the output our solar energy system would need to produce in order to power the essential items within the system. As part of our goal to make the unit serve as emergency relief, beyond that of a supplemental food source, we identified the items that would require power as the following: water pump, phone charger, miniature refrigeration system for medicine, and emergency lights. With these items identified, we were able to identify the power usage of the unit in emergency scenarios and begin planning out a solar energy system capable of supporting it. The preliminary design for the solar system architecture to support this includes a 0.8 kW PV array, 4 Trojan L16P battery, 1.5 kW inverter, and a 1.5 kW rectifier.

- **Cost**

Figure 3 illustrates the final tray system setup, showcasing the solar panel for energy autonomy, the reservoir, and the pipe arrangement for efficient plant growth.

Figure 3. HCC tray system

The total cost of constructing the HCC tray system was **$1,634.06**. The largest expenditures were:

- **PVC materials: $304.99** for PVC cell core/sch40 pipes and **$122.96** for additional PVC pipes, essential for the system's structure.
- **Solar components: $184.26** for the solar panel and **$257.96** for the solar charge controller and power inverter, enabling energy autonomy.
- **Rechargeable battery: $184.26**, used to store energy for uninterrupted operation.

Most of these materials were purchased from Amazon and Lowe’s.

2.2.2 Dutch Bucket System for Root Crops

Our second HCC design is a Dutch bucket system, which has been constructed by April 2022. This system was designed to have microgrid power capability, water collection and storage, as well as resistance to winds and flooding, as specified by the client and previous work. As seen below, the system has an 8 by 8-foot square base, along with four trapezoidal doors that can fold to 45 degrees, maximizing vertical space while minimizing wind and water stress during natural disaster events (Figure 4, 5). Inside of the system are 2, 100-watt photovoltaic (PV) modules (Figure 5, 6) as well as a four plant Dutch bucket system, and a water collection rig. Closed-cell foam material under the system provides buoyancy, designed for a 35% submergence. To ensure buoyancy remains while water is collected, the large water-collecting trashcan sits in a hole to be engulfed if full of water.

Figure 4. Floating platform, fully folded.

Figure 5. Floating platform, partially folded.

Figure 6. Floating platform, unfolded.

The electrical system is used to power the pumps in the water collection system. Also, the battery has enough extra power to charge home appliances such as refrigerators and lighting if necessary. Energy storage comes from storage in a 100 amp-hour battery, and an inverter provides 110-volt AC power for use with auxiliary needs.

- **Design Criteria**

  - **Mechanical:**

    The mechanical stress criteria are wind speeds encountered in a Category 1-3 hurricane (maximum of 129 mph) and associated storm surge. Additionally, the structure must provide a horizontal, sheltered platform to support the hydroponics system, and be positively buoyant. The constructability and affordability of the final design are also key considerations. We elected to avoid exotic materials and construction methods and stipulate that people with common hand tools and readily available building material should be able to assemble the design using basic construction skills and techniques.

  - **Electrical:**

    The electrical design criteria are to provide power for 72 hours with no solar gain. The maximum demand was estimated as 1264 watt-hours/day for two pumps, one portable refrigerator, four cell phone chargers and five LED lights. Per the National Renewable Energy Laboratory, peak sun hours at 25° latitude (approximately that of the Bahamas) is 5.5. Assuming system efficiency of 60%, 400W of instantaneous solar input is required (four 100-watt modules) for growing season energy security. A battery of 300 amp-hour capacity could provide up to three days of emergency power. A smaller 100 Ah battery was selected however, to reduce cost and overall system weight in the demonstration prototype

- **Cost**

Created during the 2023-24 academic year, the Floating HCC Platform and electrical equipment come out to $1617.00, and the Dutch bucket system costs a total of $420.37. The biggest current cost was the water collection system. The goal for this system was to make it functional, replicable and cheap. With the water pumps costing an estimated $98.00, the total cost of the water system was $189.81. The large majority of this cost was from the water pumps, which can come much cheaper. Also, if used in mass production, the cost per item would go down severely.

- **Stability and Structural Integrity**

The buoyancy of the platform was determined using hydrostatics. Autodesk Inventor was used to verify the weight and center of gravity of the assembled platform. The metacentric height was found to be positive (32.8 ft) indicating a stable platform. Although the center of buoyancy is above the center of gravity by 7.6 inches, due to the platform dimensions the center of buoyancy shifts during heeling and creates an effective righting couple.

Using Autodesk Robot Structural Analysis, we found it most effective to use ¾" plywood as the base and ½" plywood for the walls. Using this ½" plywood reduces the dead weight and is still very effective for offsetting the damage caused by wind loading. ½" plywood can withstand a 35 lb./ft2 force. Therefore, our simulated model can withstand wind speeds of up to 140 mph. The maximum pressure experienced by the platform in a category 3 hurricane is 33.85 lb./ft2, a pressure that is only experienced in concentrated areas of the platform (lower center of one of the sides, or a bottom corner). Thus, it could survive all category 3, and some category 4 hurricanes without material failure.

In the event of a more extreme event, pressure could be experienced along a larger surface if the platform were to lift such that the bottom was exposed. A majority of the wind load would be offset by the angle of the lift and in this case the platform would need to weigh a minimum of 135.4 lbs. at the perimeter creating a moment arm to counteract the wind loading force, which the platform easily exceeds. Therefore, based on our simulation, the platform is well equipped to handle a Category 3 hurricane event without tipping. Further simulations were conducted using Autodesk Computational Fluid Dynamics, analyzing the compound forces exerted on the platform by both wind and waves. The results showed resilience when exposed to Category 3 storm conditions, however limitations in our simulation software did not permit estimation of the full range of effects from wave action pitch, roll, and yaw on stability of the platform, or how these wave effects and other turbulence would reinforce wind forces on the structure. Our values are preliminary and may be updated upon further investigation. We recommend that the system be anchored to prevent loss or damage.

- **Water Collection System**

The Water Collection System (Figure 7) uses water catching, holding, and pumping to allow for plant watering when no one can tend to the system, because of a natural disaster or otherwise. This system uses three buckets: A, B and C as listed in Figure 7. During a natural disaster, the system should be closed. In this case, bucket A, the top bucket, will still be exposed to the outside world and can catch any rainwater. This bucket is connected to the system using screws, washers, and Flex Seal. On the side of this bucket, a hole with an elbow adapter and tube takes any collected water to be stored in the large trash can, labeled B. To take water from storage to the plants, a pump takes any water from trash can B to bucket C where it is dispersed to each plant using a series of tubes and adaptors. For water circulation, there is also a vacuum pump going from bucket B to trashcan C, meaning there are two pumps between these containers that take water back and forth. When the pump takes water from bucket C to B, water is pulled from the plants and circulated through the system.

Figure 7 Dutch bucket system

To test this water collection system, sprouted plants were chosen based on their nutrient needs: lettuce and carrots. The seeds for these plants were started in a greenhouse located at the University of Virginia greenhouse, to facilitate proper of timing before moving the transplants to the hydroponic system. In this system, they were placed in the Dutch buckets from April 2022 and the water circulation system was tested and used.

2.3 Comparative Performance Evaluation of HCC and CCC

- **Introduction**

We conducted a controlled comparative experiment by simultaneously planting the same number of lettuce seeds in both Hydroponic Crop Cultivation (HCC) and Conventional Crop Cultivation (CCC) systems to analyze differences in yield, growth cycle duration, and water resource consumption.

Experiment Period: March 30, 2021 – September 12, 2021
Location: Prof. Garrick Louis's backyard
Team Members: Prof. Garrick Louis, Boyang Lu, 2020-2021 Capstone Team

In the HCC system, a tray system was used for planting. Each growing tray contained 10 holes to anchor cups filled with a growing medium composed of clay and pebbles, where three lettuce seeds were planted per cup. Over the course of the study, three batches of lettuce were grown in the tray system, with the respective planting-to-harvest periods as follows: Batch 1 (03/30-05/11), Batch 2 (06/05-07/14), and Batch 3 (07/19-09/12).

The first batch primarily served to validate the functionality of the tray system for lettuce production. A series of photos taken throughout the first batch captures the growth progression of lettuce in the HCC system, which illustrate the system's capacity to support lettuce growth from seeding to maturity.

- **1st Week (Figure 8):** Early stage of seeding, showcasing the setup and growing medium used. The cups are filled with a combination of clay and pebbles to provide structural support for the seeds. Three lettuce seeds are visible in each cup, positioned to ensure even germination.
- **2nd Week (Figure 9):** Initial sprouting phase, with visible seedling development. The lettuce seedlings have emerged, showing healthy and vibrant green cotyledons. This stage highlights the effectiveness of the hydroponic system in supporting early growth.
- **3rd Week (Figure 10):** Further growth, with significant leaf expansion. The seedlings have developed their first true leaves, indicating a strong progression towards maturity. The tray system continues to provide optimal water and nutrient supply.
- **4th Week (Figure 11):** Near-mature stage, showing robust plant structure. The lettuce plants exhibit well-defined leaves with significant surface area, suggesting readiness for final growth stages.
- **5th Week (Figure 12):** Fully mature lettuce, ready for harvest. The plants have achieved their maximum size, with leaves showing consistent color and texture, making them suitable for consumption.

Figure 8 Lettuce in HCC system (1st week)

Figure 9 Lettuce in HCC system (2nd week)

Figure 10 Lettuce in HCC system (3rd week)

Figure 11 Lettuce in HCC system (4th week)

Figure 12 Lettuce in HCC system (5th week)

Figure 13 Lettuce in CCC system (2nd week)

The CCC system consisted of four 16ft^2 soil blocks. Same amount of lettuce seeds was cultivated simultaneously in both systems on June 5th. Figure 13 was taken on June 19th captures one of these blocks after two weeks of lettuce growth. The growth rate in the CCC system was significantly slower, with lettuce requiring until early September to reach full maturity. In contrast, within the same period, the tray system had already completed two full production cycles. On September 12th, all lettuce from both systems was harvested and analyzed for yield performance and other key metrics.

2.4 Results and Discussion

This section presents the comparative analysis of Hydroponic Crop Cultivation (HCC) and Conventional Crop Cultivation (CCC) systems, focusing on three performance metrics: yield, growth cycle duration, and water consumption efficiency. Table 2 provides data of three batches of HCC and one batch of CCC with respect to growth cycle duration (days), yield (lbs.), and water consumption (gallons).

Table 2 Comparative Performance Metrics of HCC and Conventional Crop Cultivation CCC.

Batch	Growing Cycle (days)	Yield (lbs.)	Water Consumption (Gallons)
CCC 1	99	0.4	90
HCC 1	42	2.6	87
HCC 2	39	2	65
HCC 3	55	3.1	90

- **Yield Analysis**
  - Higher Yield in HCC: Across the three batches, HCC produced an average of 2.57 lbs. of lettuce per batch, compared to CCC's 0.4 lbs. On average, HCC yields were 6.4 times greater than CCC yields.
  - Batch Comparisons:

    HCC 1 (42 days): Produced 2.6 lbs., 6.5 times the CCC yield.

    HCC 2 (39 days): Yielded 2.0 lbs., 5 times the CCC yield.

    HCC 3 (55 days): Delivered 3.1 lbs., 7.75 times the CCC yield.

  - Hydroponic Efficiency: The optimized nutrient delivery in HCC directly to the root zone contributed significantly to its higher productivity. The consistent control over environmental variables such as pH and nutrient concentration further supported superior yields.

- **Growth Cycle Duration**

A critical performance metric for comparing two systems is the time required to complete a growth cycle. The following observations highlight the efficiency of HCC in this regard:

- **Significant Time Reduction in HCC:** HCC completed growth cycles in 39–55 days, averaging 45.33 days per batch. In contrast, CCC required 99 days to produce a single harvest.
- **Operational Advantage:** HCC's shorter growth cycles allow for two complete harvests within the timeframe required for a single CCC cycle. This enhances annual production potential and improves resource utilization.
- **Sustainability Impact:** Shorter cycles mean faster crop turnover, enabling farmers to adapt more quickly to market demands and reducing the risks associated with prolonged exposure to pests, diseases, and adverse weather.

- **Water Consumption Efficiency**

Water usage is a crucial metric for assessing the sustainability of agricultural systems. Table 3 shows the comparison of water consumption and efficiency metrics:

Table 3 Comparison of water consumption and efficiency.

Batch	Water Consumption (gallons)	Yield-to-Water Ratio (lbs./gallon)
HCC 1	87	0.03
HCC 2	65	0.031
HCC 3	90	0.034
CCC 1	90	0.004

- **Comparable Water Use:** HCC consumed between 65–90 gallons per batch, similar to CCC's 90 gallons.
- **Superior Water Efficiency:** HCC achieved a yield-to-water ratio of 0.03–0.034 lbs. per gallon, significantly outperforming CCC's ratio of 0.004 lbs. per gallon. This represents an 8–8.5-fold improvement in water efficiency.
- **Impact on Water Sustainability:**

- The lower water requirements of HCC, coupled with its higher productivity, make it a highly sustainable solution for regions facing water scarcity.
- By reducing water waste and optimizing nutrient delivery, HCC aligns with modern agricultural goals of minimizing environmental impact.

- **Comparative Ratios**

The following ratios (Table 4) were calculated using CCC as a baseline (set to 1) to further illustrate HCC's efficiency:

Table 4 Comparative ratios of HCC relative to CCC.

Batch	Time Period Ratio	Yield Ratio	Water Consumption Ratio
HCC 1	0.42	6.50	0.97
HCC 2	0.39	5.00	0.72
HCC 3	0.56	7.75	1.00

- **Time Efficiency:** HCC consistently required 39–56% of the time needed by CCC, confirming its faster growth cycles.
- **Yield Advantage:** HCC yielded 5–7.75 times more lettuce than CCC in all cases, showcasing its vastly superior productivity.
- **Water Efficiency:** Despite using similar amounts of water as CCC, HCC's yield-to-water ratio highlights its ability to produce more with less.

- **Assessing the Potential of HCC to Substitute CCC**

Table 5 summarizes the primary agronomic and environmental factors influencing lettuce yield in both Conventional Crop Cultivation (CCC) and Hydroponic Crop Cultivation (HCC), with specific relevance to the conditions of Small Island Developing States (SIDS). Agronomic literature (Sinkovič et al., 2023) and experimental evidence indicate that the key determinants of yield per hectare include soil quality, water availability, light exposure, temperature, and humidity. These parameters are often used collectively to define productivity potential and are summarized here under the representative metric of yield per hectare.

In this study, both HCC and CCC were implemented in outdoor environments to emulate the conditions of smallholder farms in SIDS. As a result, critical environmental variables—including ambient temperature, humidity and light availability—are assumed to be equivalent across both cultivation methods. This design choice isolates the structural and operational differences between CCC and HCC systems, enabling a more focused comparison of yield-affecting factors that are not shared, such as land use, water delivery methods, and soil dependence.

Key advantages of HCC identified in Table 5 include reduced land requirements, independence from local soil fertility, and more efficient water use via closed-loop recirculation. These design characteristics allow HCC systems to support higher planting densities and shorter crop cycles, resulting in potentially greater annual yields per unit area. Meanwhile, the exposure of outdoor HCC to the same climatic fluctuations as CCC distinguishes it from climate-controlled greenhouse hydroponics, emphasizing its appropriateness for sustainable, low-energy implementation in resource-constrained settings.

This comparative framework, grounded in equal environmental exposure and clearly stated parameter assumptions, forms the basis for the subsequent parametric modeling and sensitivity analysis. These analyses are aimed at evaluating how HCC could partially or fully substitute CCC in achieving food security under a variety of yield scenarios and land availability constraints in vulnerable regions such as SIDS.

Table 5 Comparison of yield-determining factors between CCC and HCC for lettuce production in SIDS.

Factor	CCC	HCC	Impact on Yield Comparison
Land area	Limited by available arable land	Requires significantly less land	HCC can achieve higher yield per unit area
Soil type	Dependent on local soil quality and fertility	Not dependent on soil (soilless cultivation)	HCC removes soil variability as a constraint
Availability of water	Subject to rainfall and irrigation infrastructure	Efficient use of water through recirculation	HCC ensures consistent water supply
Growth cycle duration	60–90 days per cycle, seasonal	Shortened to 30–45 days per cycle, year-round possible	HCC enables more growing cycles per year

Temperature sensitivity	Dependent on ambient conditions	Exposed to ambient conditions (no active control)	Equal in SIDS
Humidity sensitivity	Dependent on ambient conditions	Exposed to ambient conditions (no active control)	Equal in SIDS
Light condition sensitivity	Dependent on ambient conditions	Exposed to ambient conditions (no active control)	Equal in SIDS

To further quantify the substitution potential of hydroponic systems in meeting food security targets, we compare the estimated land area required by CCC and HCC to produce 1,000 metric tons of lettuce—an illustrative benchmark representing a hypothetical food-secure demand level.

According to published yield data (Wikifarmer, n.d.), CCC lettuce production typically yields 20–40 tons per hectare per cycle, with a midpoint estimate of 30 tons/ha. Based on these values, the land required to meet the 1,000-ton demand using CCC ranges from:

- 50 hectares at the lower bound (20 tons/ha),
- 33 hectares at the midpoint (30 tons/ha), and
- 25 hectares at the upper bound (40 tons/ha).

By comparison, our experimental and literature-based data (Lages Barbosa et al., 2015) for outdoor HCC units indicate a yield of approximately 51 tons per hectare per cycle. To meet the same 1,000-ton demand, the required HCC land area would be:

- 1000 / 51 ≈ 20 hectares

This allows us to compute the relative land efficiency of HCC versus CCC across the range of CCC yields:

- Compared to the low-yield CCC scenario, HCC requires only 40% of the land.
- Compared to the mid-yield CCC scenario, HCC requires 61% of the land.
- Compared to the high-yield CCC scenario, HCC requires 80% of the land.

These results demonstrate that even under optimistic assumptions for CCC, hydroponic systems consistently require less land to meet the same production targets. The degree of spatial savings depends on the baseline productivity of conventional agriculture, reinforcing the importance of regional yield benchmarking when evaluating alternative cultivation technologies for food security.

To isolate the effect of cultivation method and crop cycle frequency on annual productivity, we compared the total yield per hectare per year under various CCC scenarios against that of HCC. For conventional systems, we assumed three representative scenarios based on literature-reported yields and typical seasonal planting frequencies: a low-performance scenario of 20 tons per hectare per cycle with 2 cycles per year (totaling 40 tons/hectare/year), a mid-performance scenario of 30 tons per hectare with 3 cycles per year (90 tons/hectare/year), and a high-performance scenario of 40 tons per hectare with 4 cycles per year (160 tons/hectare/year).

In contrast, the HCC system—based on our experimental and literature-supported yields—achieves 51 tons per hectare per cycle and supports 8 cycles annually, resulting in a total yield of 408 tons per hectare per year.

When comparing these values, the HCC system outperforms CCC by:

- 10.2 times under low-performance CCC conditions (40 t/ha/year),
- 4.5 times under mid-performance conditions (90 t/ha/year), and
- 2.55 times even under highly optimized CCC scenarios (160 t/ha/year).

These results clearly demonstrate that HCC systems offer significantly higher productivity per unit area, even when accounting for best-case CCC operations. This yield advantage further strengthens the case for integrating HCC into agricultural planning frameworks, particularly in regions where land availability or growing seasons are constrained by climate variability or resource limitations.

2.5 Conclusion and Future Research

This chapter made significant contributions to the design, construction, and evaluation of innovative hydroponic cultivation systems: the tray system and the Dutch bucket system. It also included a comparative analysis of these systems with Conventional Crop Cultivation (CCC). Below is a detailed discussion of the contributions:

1. **System Design and Implementation:**
   - **Tray System:**
     The tray system was designed as a solar-powered hydroponic system that optimizes nutrient delivery through a closed-loop network of PVC pipes. Each tray included multiple grow cups anchored with a clay and pebble growing medium, providing structural support and promoting healthy root development. Renewable energy was used to power the water circulation system, ensuring uninterrupted nutrient flow. This design serves as a replicable model for low-resource farming environments, particularly in regions with limited access to electricity or clean water.

- **Dutch Bucket System:**
  The Dutch bucket system focused on supporting root crops through independent water and nutrient reservoirs. Each bucket was connected to the nutrient delivery system, allowing for precise water management and reduced waste. This system demonstrated adaptability for a variety of crops, with each bucket functioning autonomously. Both systems were built with cost-effective materials and locally sourced components to ensure accessibility and affordability. The study documented the full construction process, providing a blueprint for replication.

2. **Operational Efficiency:**
   - **Growth Cycle Duration:**
     - The tray system demonstrated shorter growth cycles (39–55 days) compared to CCC's 99 days, allowing for two harvests within the time required for a single CCC cycle.
     - Faster cycles enhance crop turnover and reduce risks associated with pest infestations and adverse weather.
   - **Energy and Resource Efficiency:**
     - The use of solar panels and a rainwater collection system significantly reduced dependence on external energy and water supplies, enhancing the sustainability of the system.
3. **Hydroponic System Superiority:**
   - **Yield Performance:**
     - The tray system produced 6.4 times more yield per cycle than CCC, with a total yield of 7.7 lbs. across three cycles.
     - This highlights the ability of hydroponic systems to maximize productivity in limited space, making them particularly valuable for urban agriculture.
   - **Water Efficiency:**
     - The tray system achieved a yield-to-water ratio that was 29 times higher than CCC, demonstrating its ability to conserve water while producing significantly higher outputs.

Limitations

While this chapter provides empirical evidence that Hydroponic Crop Cultivation (HCC) systems outperform Conventional Crop Cultivation (CCC) in terms of yield per cycle, growth duration, and water-use efficiency, several limitations remain in conducting a fully standardized comparison of overall efficiency. By incorporating parametric modeling and benchmarking annualized yields under various scenarios, the analysis demonstrates that HCC can serve as a viable substitute for CCC in achieving food security, particularly in regions with land scarcity or vulnerability to climatic disruptions.

Nevertheless, certain gaps remain that warrant further research. Notably, this study does not yet incorporate comprehensive cost analyses, including lifecycle cost estimation, capital expenditures, long-term maintenance, labor requirements, and energy inputs. Without these components, it is difficult to determine the true economic feasibility and scalability of HCC systems in diverse regional contexts, especially in resource-constrained environments like Small Island Developing States (SIDS).

In addition, while annualized yield calculations were introduced to improve the comparability of HCC and CCC systems, other key factors such as post-harvest handling efficiency, nutrient use efficiency, and labor productivity have not been rigorously quantified. These dimensions are essential for developing a holistic understanding of the sustainability and operational feasibility of hydroponic systems.

To address these gaps, future research should adopt a standardized evaluation framework that includes: (1) normalization of yield data across spatial and temporal scales (e.g., kilograms per hectare per year); (2) life-cycle cost accounting, including amortized infrastructure and equipment costs; (3) detailed inventories of labor, energy, and nutrient inputs; and (4) environmental impact metrics such as carbon footprint or resource use intensity. Establishing such a framework will support more transparent and replicable evaluations of the trade-offs and benefits of hydroponic versus conventional cultivation systems.

By expanding the analytical scope to include these factors, future work can build on the foundation laid in this chapter to provide even more robust guidance to farmers, policymakers, and development agencies considering climate-resilient agricultural investments.

Author Contributions

This project originated as a Capstone design effort led by undergraduate students in the Systems Engineering program. Garrick E. Louis and Boyang Lu served as faculty and graduate mentors, providing conceptual guidance and technical oversight. In addition to mentoring responsibilities, Boyang Lu played a central role in shaping the research objectives, designing the experimental framework, and developing the methodology for evaluating system performance. He actively contributed to the construction and testing of the hydroponic systems, performed the comparative data analysis between hydroponic and conventional cultivation methods, and led the drafting and technical refinement of the manuscript. The undergraduate co-authors were primarily responsible for system prototyping, data collection, and preliminary analysis. All authors contributed to the review and approval of the final manuscript.

Chapter 3

Addressing Schedule Risks in the Process of A Multi-Period Production-Inventory System

Published in Proceedings of the American Society for Engineering Management 2020 International Annual Conference

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Abstract

Hydroponic Crop Cultivation (HCC) can complement conventional soil-based crop cultivation for food security in the face of land and water restrictions associated with climate change. However, there is a lack of methodological studies on the food chain for these crops as they move from farm to table. Of particular importance are the risks to processing facilities as these are potential chokepoints in the food chain. Risks may significantly impact the overall production and inventory schedules, the delivery of finished products, and ultimately adversely affect the profit of enterprises. Therefore, it is important to identify and address risks in the food processing system to assure its optimal performance. This paper identifies potential schedule risks in the HCC production-inventory system and integrates the risks into a stochastic model to optimize the production-inventory schedule for the entire system. Our goal is to determine the production quantity, inventory level, and energy consumption in each time period so that the total cost for the entire food processing system is minimized. Firstly, we use the Integrated Definition (IDEF) method to identify uncertain food demand and fluctuating energy supply as two major sources of risks for the HCC production-inventory system. Secondly, a stochastic model is introduced to optimize the multi-period production-inventory schedule for the system. Finally, a numerical experiment is carried out to verify and validate the model.

Keywords: Risk identification; hydroponic crop cultivation; production-inventory schedule; energy resources; stochastic model.

3.1 Introduction

The risks of operating HCC systems come from many sources, especially interruptions to the power supply. Electricity keeps the HCC equipment running, including the water pump, lighting and any necessary temperature and humidity control systems. An unstable power supply may decrease the production rate of HCC systems. A serious power outage may even cause the roots of crops to die from lack of oxygen. HCC companies need to consider the risk of electric power disruptions and its effect on matching their supply of products to consumer demand. Disruptions in supply can lead to a decrease in customer satisfaction, which adverse profits. On the other hand, uncertainties in consumer demand must be considered in production planning since overproduction can lead an increase in production cost. An inventory of products may be used to dampen short-term mismatches in supply and demand, especially in the face of supply uncertainties introduced by production risks like power interruptions and the variability in consumer demands.

Extant research has not provided guidance on how HCC companies should respond to risks the production process or the scheduling of inventory. To help HCC enterprises minimize the total cost in the production-inventory schedule and enhance their competitiveness, we propose a stochastic model to optimize a multi-period production-inventory schedule that addresses potential risks. Section 2 is a review of relevant literature on the risk identification method we will use and the stochastic production-inventory model we will build. In Section 3, we identify potential risks in the process of HCC production and inventory. In Section 4, we present a multi-period production-inventory model that integrates the identified risks and seeks to minimize the total cost of the system. Section 5 provides a numerical experiment to validate the model and a discussion of the results. Section 6 is a conclusion, including the limitations of this work.

We begin our review with a discussion of Integrated Definition Methods (IDEF) and their use in stochastic production-inventory models.

IDEF was conceived by the United States Air Force and developed in the mid-1970s. It was developed as a primary tool for recording and evaluating business processes (Lambert, Jennings & Joshi, 2006). Three techniques were developed to define IDEF at that time:

1) IDEF0. It is a structured representation of functions, activities, or processes within a modeled system or subject area (Lambert et al., 2006).
2) IDEF1. It captures the information that exists about objects within the scope of an enterprise (Lu et al., 1996). The IDEF1 perspective of an information system includes the automated system components and the non-automated objects, such as people, filing cabinets and telephones.
3) IDEF2. It is a method for representing the time varying behavior of resources in a manufacturing system, providing a framework for specification of math model-based simulations (IDEF2 Simulation Model Design, 2010).

In this paper, we use IDEF0 to identify risks existed in the HCC production-inventory system. Here, we analyze the strengths and weakness of IDEF0 before we use the method. There are four main strengths of IDEF0. Firstly, the model has proven effective in detailing the system activities for function modeling. Secondly, IDEF0 models provide an abstraction away from timing, sequencing, and decision logic. However, it is easy to use IDEF0 for modeling activity sequences whenever needed. For instance, it is easy to order the activities in the system from left to right in the decomposition diagram (The Complete Guide to Understand IDEF Diagram, n.d.). Thirdly, IDEF0 provides a concise description of the system by using the ICOMS (Inputs, Controls, Output, Mechanism) framework. Fourthly, the hierarchical nature of IDEF0 allows the system to be easily refined into greater detail until the model is as descriptive as necessary for the decision-making task.

Additionally, there are two main weaknesses in IDEF0. Firstly, IDEF models might be so concise that only domain experts can understand them. The abstraction away from timing, sequencing and decision logic leads to comprehension difficulties for people outside the domain. Secondly, getting input from subject matter experts requires that the facilitator understand all the details of IDEF modeling.

In this paper, we also present a multi-period stochastic HCC production-inventory system and integrate the risks into a stochastic model to optimize the production-inventory schedule for the entire system. Under an uncertain decision-making environment where the probability distributions of stochastic parameters are known, scenario-based stochastic programs have been widely used for designing/redesigning supply chain networks. (Govindan et al., 2017; Melo et al., 2009; Snyder, 2007). Below we revisit several models that are closely related to our work.

Federgruen and Zipkin (1984) optimize a stochastic production program for a central plant that fulfills random demands from several locations. They minimize the expected holding and backorder cost over a finite number of time periods. Lee and Yano (1988) develop a back-track dynamic programming method to find the optimality of a serial production system with the goal to minimize operating, holding, and backorder costs subject to random yield. Wang and Gerchak (1996) further generalize the random yield model by incorporating capacity variability. Kira et al. (1997) propose a hierarchical method to optimize a multi-period, multi-product production scheduling problem under a finite set of demands using stochastic linear programming. Armentano et al. (2001) address the lot-sizing problem in capacitated multistage systems by minimizing production, inventory, and setup costs based on the Wagner-Whitin algorithm. Duran et al. (2007) design an optimal production and inventory policy assuming general stochasticity for demand and production. Kogan (2009) investigates a basic production planning problem under multiplicative stochastic yield and additive stochastic demand. Singer and Khmelnitsky (2010) consider optimal production control of a one product- type production inventory system where demand is a discrete-time stochastic process. Higle and Kempf (2010) propose a stochastic programming model for production planning under both supply and demand uncertainty via Markov decision process. Geunes et al. (2011) propose approximation algorithms for more generalized class of supply chain and logistic models under deterministic and stochastic demands are studied. Georgiadis et al. (2011) developed a two-stage model in which location decisions for warehouses and distribution centers should be made. Cheng et al. (2012) optimize a hybrid two-stage push-pull production system with uncertain peak demand subject to the service level constraints. Zhang et al. (2016) study the Dynamic multi-technology production-inventory problem with emissions trading. Govindan and Fattahi (2017) propose a two-stage stochastic model to determine the location of the production plants and warehouses. Fattahi et al. (2018) propose a multi-stage stochastic program for supply chain network redesign problem with price-dependent uncertain demands. Li and Hu (2020) develop a multistage stochastic programming model for farmland irrigation management under uncertainty.

This brief review shows that there is precedent to handle the problem of production with stochastic interruptions that influence supply and uncertain consumer demand. We draw on this precedent to address these challenges faced by HCC companies.

3.2 Methodology

3.2.1 Risk Identification Method

In this section, we will identify risks associated with the HCC system from production, storage and distribution. Lambert et al. (2005) proposed a risk identification method for detecting risks in large-scale engineering systems. We took 5 steps to adapt this work to our study:

Step 1. Identify the components of the HCC production and inventory system

Step 2. Identify system incidents

Step 3. Identify system components that participate directly with a given incident

Step 4. Identify system components that participate indirectly with a given incident

Step 5. Analyze the cause of incidents and define the source of risk

In step 1, we identified the components of the system from the process of product circulation, production, storage and distribution. Table 6 lists descriptions of pertinent system components.

Table 6 System components for HCC production-inventory system.

Circulation Process	Components
Production	Equipment
	Labor
	Electric energy (supply & price)
	Nutrient solution

	Seeds
	Food (quantity & quality)
Storage	Warehouse
Distribution	Food Market
	Transportation

In step 2, we identify the potential incidents which may occur from production to distribution in the system. In step 3 and 4, we need to identify the direct and indirect interactions between components and incidents. Table 7 shows 8 system incidents with descriptions, severity, components in direct and indirect interactions. We rank the severity of incidents according to their expected impact on the system production-inventory schedule.

Table 7 Incidents, interactions and severity.

	Incident	**Components in direct interaction**	**Components in indirect interaction**	**Description**	**Severity**
1	System failure	Equipment		Equipment failure, such as cooling/heating system failure, may kill plants in few days.	Medium/High
2	System failure	Labor		The lack of skill level of the workers can cause the system to fail to operate properly.	Low
3	System failure	Electric energy (supply)		Unstable power supply may cause system outages.	High
4	Schedule changed		Electric energy (price)	Fluctuating energy prices may change the production-inventory schedule.	High
5	Overstock	Food production & demand, warehouse		Food production is far greater than demand.	High
6	Shortage of stock	Food production & demand, warehouse		Food production is much smaller than demand.	High

7	Food loss	Transportation & storage		Food loss may occur during inventory and transportation	Low
8	Nutrient loss		Nutrient solution	Nutrient loss may occur because nutrients were not fully absorbed by root of crops.	Low

In this paper, we regard high-severity incidents (3, 4, 5 and 6) as the major risks when optimizing the production-inventory schedule to achieve minimum cost for the system. In step 5, we conclude that incidents 3 and 4 were caused by a fluctuation energy supply, while incidents 5 and 6 are caused by the uncertainty of food demand. Consequently, we can conclude that a fluctuating energy supply and uncertainty in food demand are two major risks for HCC companies to make decisions for production-inventory schedule.

Next, we aim to integrate these two risks into the production-inventory model. Integrated Definition (IDEF) is a method used by enterprises to model and analyze different types of processes and activities. Thorisson et al. (2019) modified the IDEF modeling format with risk identification incorporated, as illustrated in Figure 14.

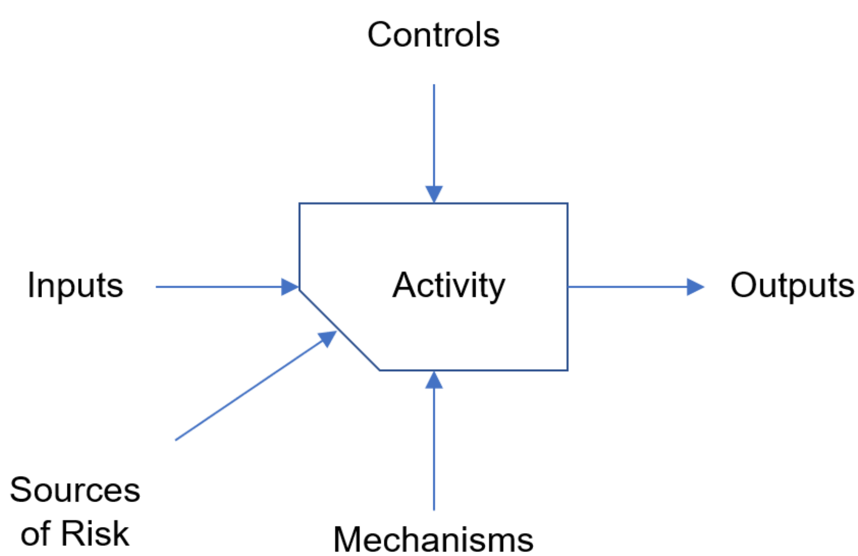

Figure 14 Modified IDEF modeling format with risk identification.

Based on this method, we integrate fluctuating energy supply and uncertainty in food demand as two sources of risk into the production-inventory model, which can be seen in Figure 15.

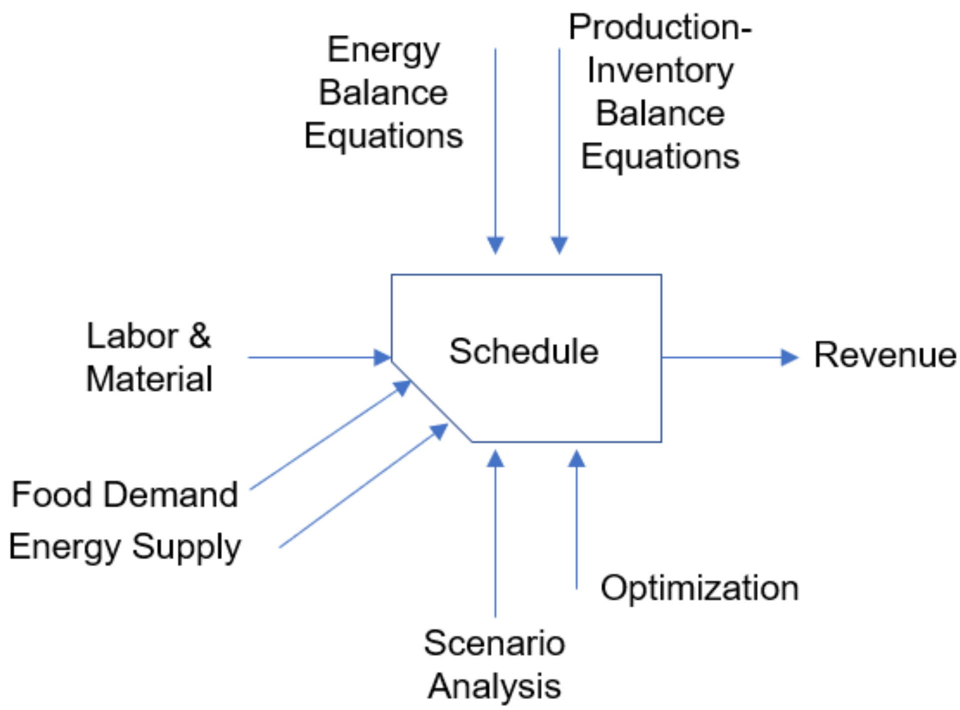

Figure 15 HCC production-inventory system with risk identification.

In this model, we input labor and material to produce food in the HCC system. Uncertain food demand and unstable energy supply are two major sources of risk for each production-inventory cycle. Decision makers should optimize the production-inventory schedule by ensuring both energy supply and a balance between production and inventory to maximize profit or minimize cost of the HCC enterprise.

3.2.2 Scenario Decision Tree

We regard the production-inventory process of a manufacturing company as several sequential periods. A multi-period model allows several layers of decisions, where at each time period more random outcomes are realized. The uncertainties over a planning horizon with multiple periods can be captured by a scenario tree (Birge and Louveaux, 2011; Kall, 2011).

We denote T as the set of time periods and $t = 1,2,\dots,T$ as the index for each time period. At the beginning of each period, assume that we know the amount of available energy for the current period. However, we are uncertain about the demand for each period because of unpredictable factors that affect short-term consumer preferences. These include the price of related goods, such as other types of fruits and vegetables and weather, which affects shopping and cooking behavior. However, we can assume the demand in the form of scenarios.

Table 8 lists the stochastic parameters associated with the scenario tree. Let Ω_t denote the set of scenarios for time period t, and each scenario in Ω_t be indexed by ω_t . In addition, each scenario is associated with probability p^{ω_t}. We define $p^{\omega_0} = 1$ for $t = 0$. To illustrate the idea, Figure 16 depicts a scenario tree with two scenarios in period 1, four scenarios in period 2, and 2^t scenarios in period t. Note that ω_t in the scenario tree has a corresponding ancestor scenario ω_{t-1}, denoted by $a(\omega_t)$. Additionally, the value of p^{ω_t} is a joint probability of all ancestor scenarios of ω_t on the path from the root ω_0 to ω_t.

Table 8 Stochastic parameters.

Symbol	Description
ω_t	A scenario in period t
Ω_t	Set of all possible scenarios ω_t
$a(\omega_t)$	The corresponding ancestor scenario ω_{t-1} of scenario ω_t
$D_t^{\omega t}$	Demand of scenario ω_t in period t
$G_{1,t}$	Available energy 1 in period t
$G_{2,t}$	Available energy 2 in period t
p^{ω_t}	Probability of scenario ω_t in period t

To make a manufacturing schedule of the production, we need to make decisions about the production quantity, inventory level and the amount of energy use before the beginning of the current period. This can be assumed based on the value of these parameters at the end of the scenario in the last period. However, the consumption of energy happens in the current period. The decisions corresponding to each branch from the root to each scenario in the final period are listed on the right side of Figure 16. The detailed explanation of these decision variables is provided in Table 9.

Table 9 Decision variables in scenario tree

Symbol	Description
$x_t^{\omega_{t-1}}$	Production quantity in period t under scenario ω_{t-1}
$q_t^{\omega_{t-1}}$	Inventory level at the end of the period t under scenario ω_{t-1}
$v_t^{\omega_{t-1}}$	Backorders at the end of period t under scenario ω_t
$y_{1,t}^{\omega_t}$	Energy 1 consumed in period t under scenario ω_t
$y_{2,t}^{\omega_t}$	Energy 2 consumed in period t under scenario ω_t

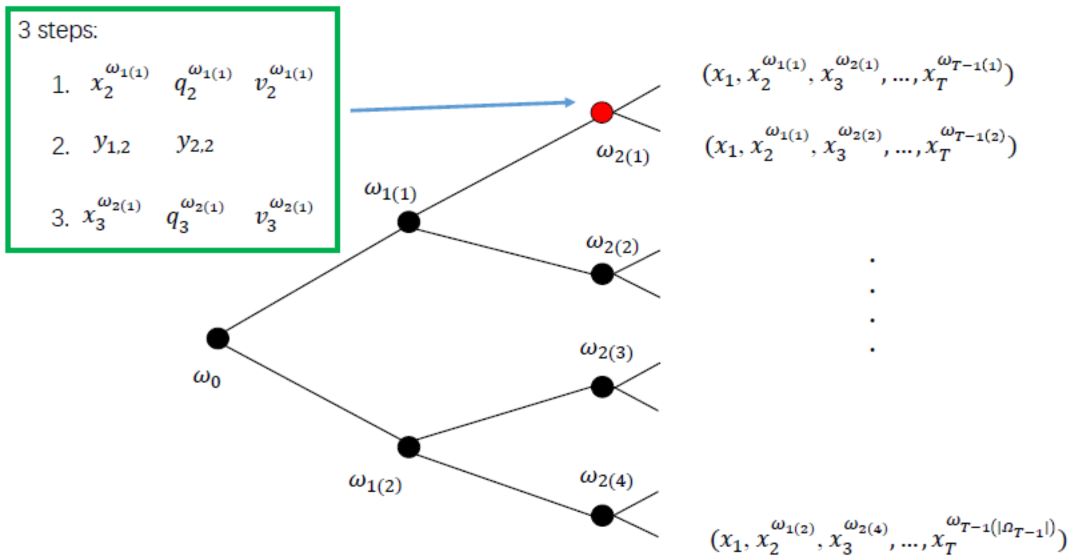

Figure 16 Scenario tree for production-inventory model

Let us use scenario $\omega_{2(1)}$ as an example to explain the process of production. There are three steps related to this scenario. Firstly, at the end of the scenario $\omega_{1(1)}$ (which occurs in $t = 1$), we need to make decisions about the production quantity $x_2^{\omega_{1(1)}}$, the inventory level $q_2^{\omega_{1(1)}}$ and the amount of energy use. Secondly, in the period $t = 2$, based on the decision we made in step 1, we continue production by consuming energy and acquiring information of the energy consumption $y_{1,2}$ and $y_{2,2}$. Thirdly, at the end of scenario $\omega_{2(1)}$, we make decisions for next time period.

In general, the uncertainties in the whole production-inventory system come from the different decision in response to the different demands for each scenario, including the production quantity, the inventory level, and the amount of energy supply.

3.2.3 Approach to Estimate Energy Prices

We regard the energy price as a variable for each period that is not a constant. Therefore, we need to estimate the energy price for each period by using regression analysis. We do these four steps as follows:

Step 1. Collect the historical data of energy price for each time period.
Step 2. Add different types of trendlines (e.g.: linear, logarithmic, polynomial, power and exponential) for the data and identify the function of each trendline using regression analysis.

Step 3. Compare the goodness of fit for each type of trendline by calculating the coefficient of determination R^2.

Step 4. Select the trendline with the value of R^2 which is closest to 1 and use the function of this trendline as the energy price function for estimation.

3.3 Mathematical Model

To facilitate the problem formulation, the parameters are provided in Table 10.

Table 10 Model parameters

Symbol	Description
c	Material and labor cost of making product
h	Unit holding cost for product
π	Backorders cost for product
$g_{1,t}$	Energy 1 price in period t
$g_{2,t}$	Energy 2 price in period t
E	Energy consumed for making one unit of product

$$\mathbf{min} \sum_{t\epsilon T}\sum_{\omega_{t-1}} p^{\omega_{t-1}}\left(cx_t^{\omega_{t-1}} + hq_t^{\omega_{t-1}} + \pi v_t^{\omega_{t-1}}\right) + \sum_{t\epsilon T}\sum_{\omega_t} p^{\omega_t}\left(g_{1,t}y_{1,t}^{\omega_t} + g_{2,t}y_{2,t}^{\omega_t}\right) \quad (1)$$

$$\boldsymbol{s.t.}\ x_t^{\omega_0} - q_t^{\omega_0} + v_t^{\omega_0} \geq D_t^{\omega_t},\ t \in \{1\} \quad (2)$$

$$x_t^{\omega_{t-1}} + q_{t-1}^{a(\omega_{t-1})} - q_t^{\omega_{t-1}} - v_{t-1}^{a(\omega_{t-1})} + v_t^{\omega_{t-1}} \geq D_t^{\omega_t}, \quad \forall t \in T\{1\}\ and\ \omega_{t-1} \in \Omega_{t-1} \quad (3)$$

$$Ex_t^{\mathrm{a}(\omega_t)} = y_{1,t}^{\omega_t} + y_{2,t}^{\omega_t}, \quad \forall t \in T\ and\ \omega_t \in \Omega_t \quad (4)$$

$$y_{1,t}^{\omega_t} \leq G_{1,t}, \quad \forall t \in T\ and\ \omega_t \in \Omega_t \quad (5)$$

$$y_{2,t}^{\omega_t} \leq G_{2,t}, \quad \forall t \in T\ and\ \omega_t \in \Omega_t \quad (6)$$

$$x_t^{\omega_{t-1}},\ q_t^{\omega_{t-1}}, v_t^{\omega_{t-1}} \geq 0, \quad \forall t \in T\ and\ \omega_{t-1} \in \Omega_{t-1} \quad (7)$$

$$y_{1,t}^{\omega_t}, y_{2,t}^{\omega_t} \geq 0, \quad \forall t \in T\ and\ \omega_t \in \Omega_t \quad (8)$$

The objective (1) is to minimize the total costs comprised of non-energy and energy related expenses. Non-energy cost items include production, inventory holding and backorder costs. Energy costs include the consumption cost of two energy, which represent grid renewable energy and grid conventional energy. Constraints (2) and (3) are the fundamental production-inventory balance equations capturing the relation among production, demand, inventory, and backorders. Constraint (4) is the energy balance equation ensuring that the total energy consumed in period t is equal to the sum of consumption of the energy 1 and 2. Constraints (5) and (6) define the supply limitations for both energies. Finally, constraints (7) and (8) simply state the nonnegative requirements for all the decision variables.

3.4 Results and Discussion

In this section, we perform a numerical experiment to demonstrate the application of the proposed production planning model. The numerical example was solved by Python. The assumed historical energy prices for each time period are shown in Table 11 and Figure 17.

Table 11 Historical energy price

Period	Energy 1 Price	Energy 2 Price
1	0.05	0.08
2	0.06	0.04
3	0.08	0.09
4	0.07	0.07
5	0.09	0.06
6	0.04	0.06
7	0.03	0.08
8	0.06	0.10
9	0.08	0.11
10	0.10	0.09

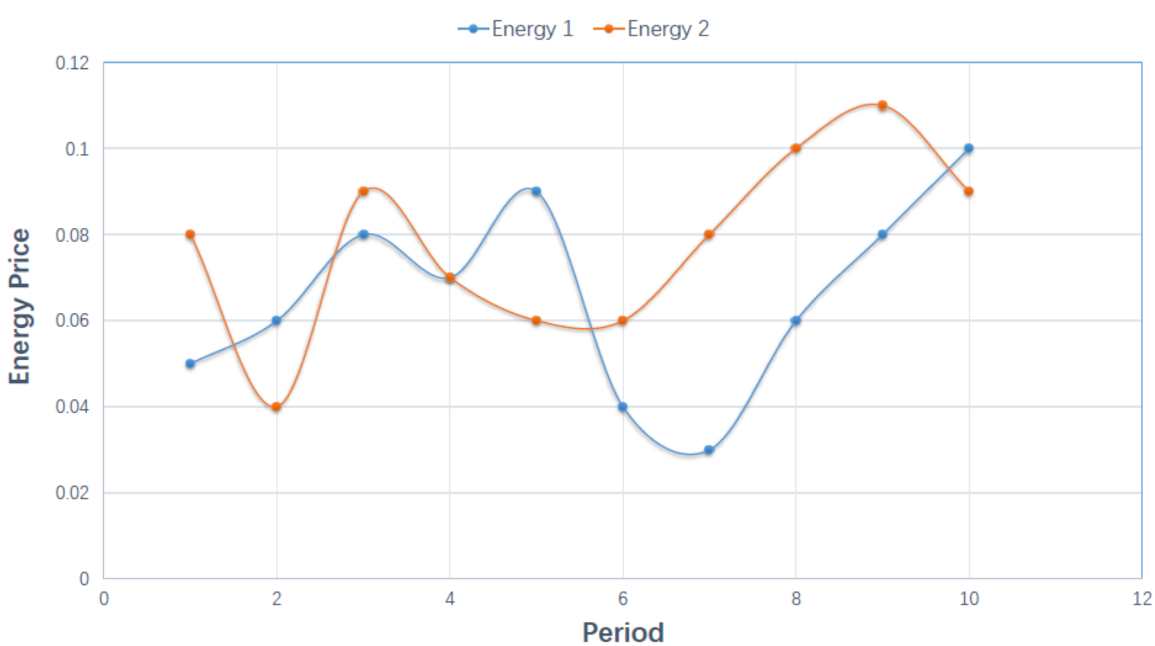

Figure 17 Historical energy price for each time period

To estimate the current energy price, we use Excel to do the regression analysis. We first add the polynomial trendline for two kinds of energy and display the trendline equation. It is shown in Figure 18.

- Polynomial trendlines:
$$g_{1,t} = -9E - 0.6t^6 + 0.0002t^5 - 0.0012t^4 - 0.0001t^3 + 0.0256t^2 - 0.0476t + 0.0743 \quad (R^2 = 0.8165)$$
$$g_{2,t} = 5E - 0.5t^6 - 0.0017t^5 + 0.0233t^4 - 0.01549t^3 + 0.5198t^2 - 0.8075t + 0.5 \ (R^2 = 0.9136)$$
- Linear trendlines:
$$g_{1,t} = -0.0019t + 0.0553 \ (R^2 = 0.0699)$$
$$g_{2,t} = 0.004t + 0.056 \ (R^2 = 0.3333)$$
- Exponential trendlines:
$$g_{1,t} = 0.0554e^{0.021t} \ (R^2 = 0.0284)$$
$$g_{2,t} = 0.0555e^{0.055t} \ (R^2 = 0.3101)$$
- Logarithmic trendlines:
$$g_{1,t} = 0.0073\ln(t) + 0.055 \ (R^2 = 0.0581)$$
$$g_{2,t} = 0.0128\ln(t) + 0.0586 \ (R^2 = 0.2015)$$

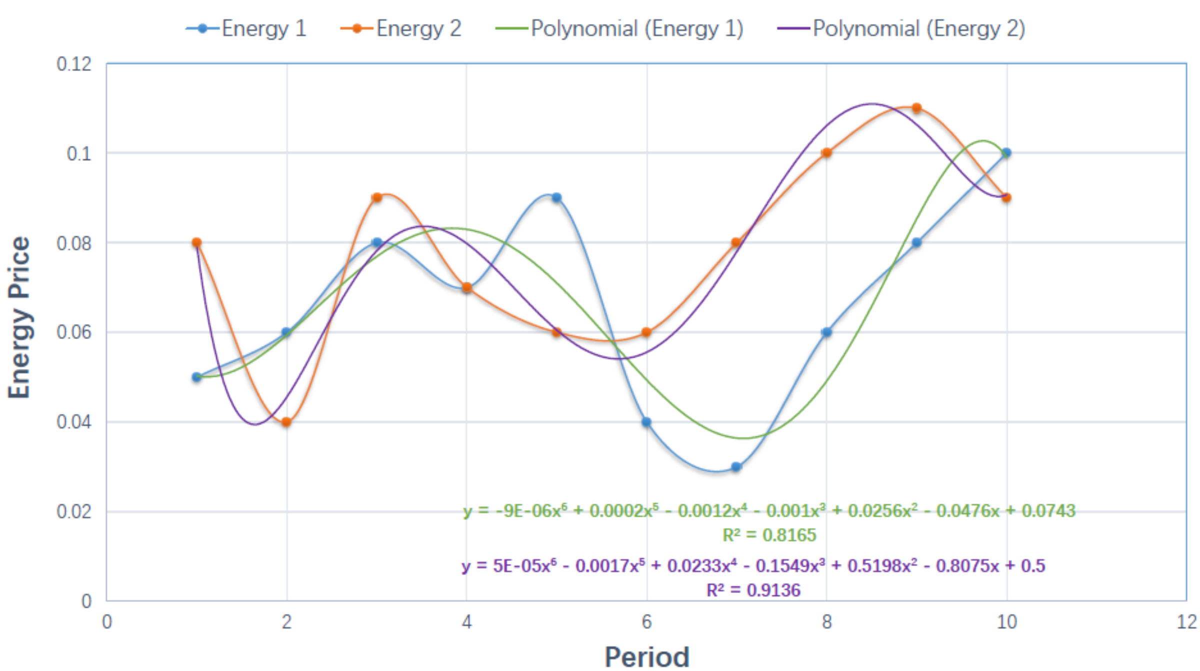

Figure 18 Regression analysis by polynomial trendlines

Since polynomial trendlines have the maximum value of R^2, we choose these two polynomial equations as $g_{1,t}$ and $g_{2,t}$, respectively.

The assumed value of the parameters in this experiment are listed in Table 12:

Table 12 Problem settings

Symbol	Value
T	10
c	13
h	2
π	15
E	20
$D_t^{\omega t}$	A random value between [800,1200], $\forall t \in T \text{ and } \omega_t \in \Omega_t$
$G_{1,t}$	$G_{1,t}$ =9000,10000,11500,8500,7000,12500,14000,8000,7000 for t =2,3,…,10
$G_{2,t}$	$G_{2,t}$ =11000,9000,9000,13500,13000,9000,8000,11000,12500 for t =2,3,…,10
p^{ω_t}	$p^{\omega_t} = \frac{1}{2^{t-1}}\ \forall t \in T \text{ and } \omega_t \in \Omega_t$

Figures 19 and 20 present the optimal production, inventory, and energy consumption levels for a multi-period Hydroponic Crop Cultivation (HCC) production-inventory system under uncertain energy supply and demand fluctuations. The results illustrate how the stochastic optimization model dynamically adjusts production and inventory decisions in response to variations in energy availability and consumer demand, thereby minimizing total system costs.

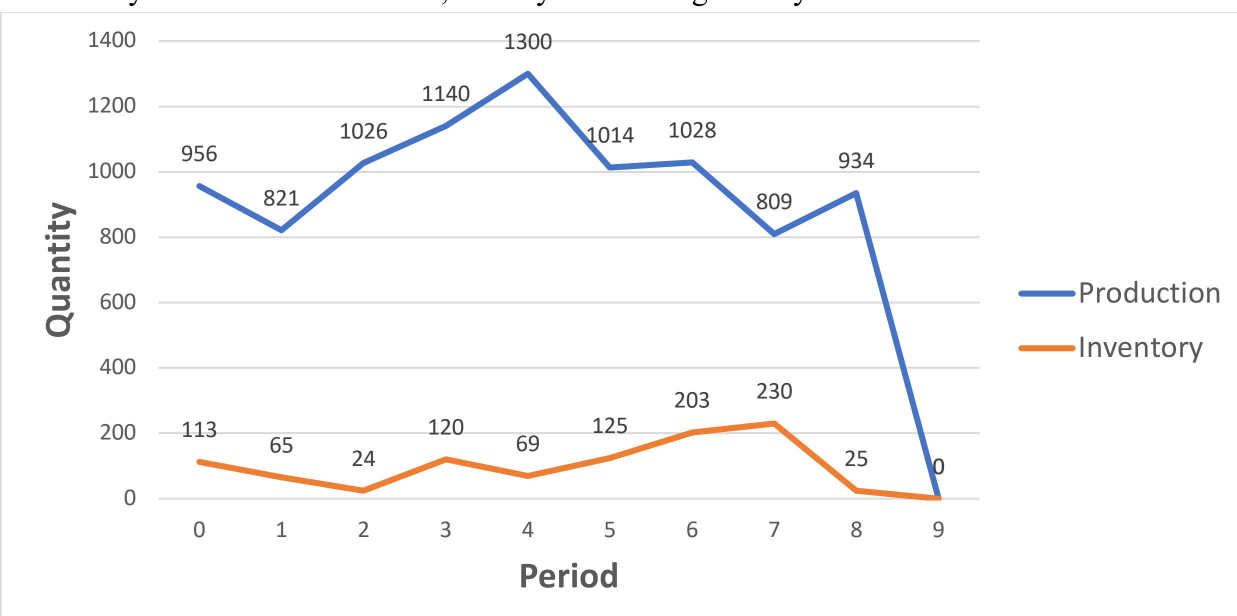

Figure 19 Production quantity and inventory level for optimal strategy.

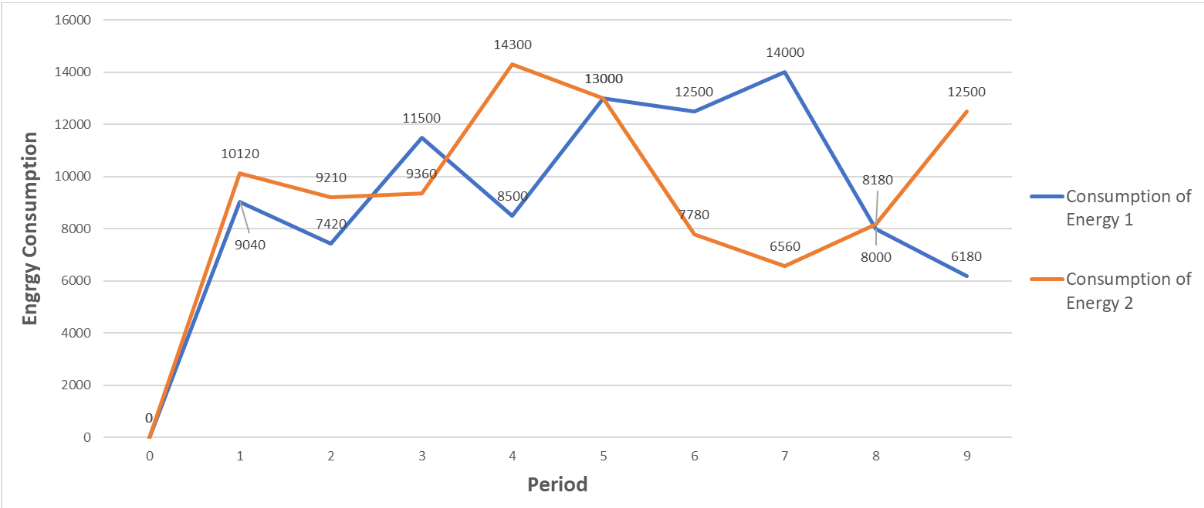

Figure 20 Energy consumption for optimal strategy.

3.4.1 Production and Inventory Decisions

The optimal production and inventory levels exhibit distinct patterns over the ten time periods, reflecting strategic adjustments to demand fluctuations and energy price variations. The key observations from the results are as follows:

- **Initial Production Strategy (Periods 0-4):** The system starts with an initial production of 956 units in Period 0 with an inventory level of 113. Production fluctuates slightly, reaching its highest at 1300 units in Period 4, as the system balances demand and energy costs. Inventory levels remain relatively low in these periods, peaking at 120 in Period 3, indicating a just-in-time production strategy that minimizes holding costs while ensuring product availability.
- **Mid-Term Adjustments (Periods 5-7):** A shift in strategy is observed in Period 7, where inventory reaches its highest level at 230 units. This suggests a stockpiling approach, in anticipation of increased demand. Production levels during these periods remain consistent, averaging around 984 units.
- **Final Period Strategy (Periods 8-9):** In the last two periods, production drops significantly, with Period 9 showing zero production, indicating a system shutdown. Inventory is gradually depleted, ending at zero in the final period, ensuring that no excess stock is held unnecessarily.

These results underscore the model's ability to dynamically adjust production and inventory levels in response to demand uncertainties and operational constraints. The system prioritizes efficiency by maintaining lean inventory levels while preventing supply shortages through adaptive production scheduling.

3.4.2 Energy Consumption Optimization

The model effectively manages energy consumption by dynamically adjusting the usage of Energy 1 (lower-cost renewable energy) and Energy 2 (higher-cost conventional energy) to minimize total operating expenses. The results reveal key insights:

- **Energy Usage Trends:** Energy consumption fluctuates significantly across periods, reflecting dynamic adjustments to optimize costs. The highest energy consumption for Energy 1 is observed in Period 7 (14,000 kWh), while Energy 2 peaks in Period 4 (14,300 kWh). This suggests that the model prioritizes renewable or lower-cost energy sources when available but shifts to alternative sources when necessary.
- **Periods of Low Energy Use:** In Period 9, total energy consumption drops to 18,680 kWh (6,180 kWh from Energy 1 and 12,500 kWh from Energy 2), reflecting the corresponding production shutdown. The initial period (Period 0) also records zero energy consumption, aligning with startup conditions.
- **Energy Allocation Strategy:** The system consistently favors Energy 1, particularly in periods where production is high (Periods 3, 5, and 7). However, during periods of increased production uncertainty (e.g., Period 4), Energy 2 usage spikes, indicating a shift to more stable but potentially costlier energy sources.

These findings validate the effectiveness of integrating stochastic energy supply variability into production-inventory planning. The results suggest that hydroponic crop cultivation enterprises should prioritize investment in renewable energy storage and forecasting tools to optimize energy costs and enhance system resilience.

3.4.3 Policy Implications for HCC Enterprises

1. **Strategic Inventory Management for Risk Mitigation**
   - The findings highlight the importance of maintaining limited but flexible inventory buffers to smooth production fluctuations. Decision-makers in HCC operations should incorporate dynamic inventory strategies, particularly in periods where production uncertainty is high.
2. **Energy-Efficient Production Scheduling**
   - The optimal schedule suggests that maximizing renewable energy consumption during periods of abundance can substantially reduce operating costs. Enterprises should invest in energy forecasting tools and flexible production scheduling to capitalize on lower-cost renewable energy availability.
3. **Adaptive Production Planning for Demand Uncertainty**
   - The model demonstrates that production should not remain static but instead respond dynamically to demand fluctuations. HCC enterprises should implement real-time demand forecasting and flexible manufacturing strategies to adapt to market conditions while minimizing waste.
4. **Economic Justification for Renewable Energy Investments**
   - The model's preference for utilizing Energy 1 (renewable) whenever available highlights the long-term cost savings associated with increasing renewable energy adoption in HCC operations. This supports policy recommendations advocating for

investment in solar microgrids and energy storage solutions to enhance operational resilience.

3.5 Conclusion and Future Research

This study presents a stochastic optimization model designed to enhance the resilience and cost-efficiency of Hydroponic Crop Cultivation (HCC) production-inventory systems under conditions of uncertainty. By integrating key risk factors, fluctuations in energy supply and variability in consumer demand, the proposed framework provides a structured approach for minimizing total operational costs while maintaining system stability and responsiveness.

This research advances the understanding of risk-aware decision-making in hydroponic agricultural systems by making the following key contributions:

1. **Development of a Stochastic Optimization Model for HCC Production-Inventory Scheduling**
   One of the primary contributions of this study is the formulation of a stochastic optimization model that explicitly incorporates uncertainty in energy supply and consumer demand into production-inventory decision-making. Unlike deterministic models that assume a stable operating environment, this framework accounts for real-world volatility, enabling HCC enterprises to dynamically adjust production levels, inventory management, and energy consumption in response to stochastic fluctuations. This approach enhances system robustness, reduces waste, and minimizes cost inefficiencies.

2. **Risk Identification and Quantification in HCC Operations**
   This study systematically identifies and quantifies the key risks that impact hydroponic crop production, particularly focusing on energy supply instability and demand uncertainty. Using the Integrated Definition (IDEF) method, we classify and rank potential disruptions based on severity and frequency, thereby providing an analytical foundation for understanding how these risks propagate through the production-inventory system. By integrating these risks into the stochastic optimization model, this study offers a more realistic and actionable decision-support tool for industry stakeholders.

3. **Optimization of Energy-Dependent Production-Inventory Decisions**
   Hydroponic farming is highly dependent on electricity for maintaining optimal growing conditions, making energy costs a critical determinant of profitability. This study introduces a novel energy-aware optimization strategy that balances the trade-offs between grid energy usage, inventory buffering, and production planning. The model's ability to dynamically adjust operations based on projected energy price fluctuations ensures cost-effective resource utilization, making it particularly valuable in regions where energy pricing is volatile or subject to supply disruptions.

4. **Empirical Validation Through Numerical Experiments**
   To validate the effectiveness of the proposed model, this study conducts a series of numerical experiments simulating real-world scenarios of energy price variability and demand fluctuations. The results demonstrate that the optimized production-inventory schedule significantly outperforms conventional heuristics in minimizing total operational costs while maintaining supply chain stability. These findings provide quantitative evidence of the model's practical value and establish a benchmark for future research on risk-aware agricultural optimization.

5. **Theoretical and Practical Contributions to Agricultural Resilience**
   By integrating stochastic optimization techniques with production-inventory scheduling, this research bridges a crucial gap in the literature on risk management in controlled-environment agriculture. The insights generated extend beyond hydroponic farming, offering broader applications in other energy-intensive agricultural production systems, such as vertical farming and greenhouse-based cultivation. Moreover, the study's practical implications offer actionable strategies for farmers, agribusiness leaders, and policymakers seeking to enhance food security and agricultural sustainability under conditions of environmental and economic uncertainty.

Limitations and Directions for Future Research

Despite its contributions, this study has several limitations that warrant further investigation:

1. **Scope of Risk Consideration**
   This study primarily focuses on high-severity risks, such as major power outages and significant demand fluctuations. However, low-severity risks—including incremental equipment degradation, logistical inefficiencies, and evolving consumer preferences—can cumulatively exert substantial influence on production planning and cost structures. Future research should develop a more comprehensive risk taxonomy to account for both acute and chronic disruptions.

2. **Interdependencies and Cascading Effects of Risks**
   The current model assumes risk factors to be independent; however, in real-world scenarios, disruptions often exhibit interdependencies. For instance, power outages may not only halt production processes but also compromise the efficacy of climate control systems, thereby affecting crop health and yield stability. A more refined approach would involve modeling cascading risk effects and assessing their systemic implications.

3. **Empirical Validation and Real-World Implementation**
   Although this study demonstrates the model's validity through numerical simulations, its practical applicability remains to be tested in operational HCC enterprises. Empirical field studies are necessary to evaluate the model's performance in live production

environments, enabling refinements that account for real-world constraints such as labor availability, regulatory requirements, and technological adoption barriers.

4. **Integration with Renewable Energy Systems**
   Given the significant energy dependency of HCC systems, integrating renewable energy sources—such as solar microgrids and battery storage solutions—could further enhance operational resilience. Future research should explore the cost-benefit trade-offs of renewable energy adoption in HCC facilities and develop hybrid energy management strategies that optimize both economic and environmental sustainability.

Chapter 4

Enhancing Agricultural Resilience to Hurricanes: Evaluating the Adoption and Impact of Hydroponic Crop Cultivation Using System Dynamics

In Review by Environment, Development and Sustainability.

Boyang Lu, Garrick E. Louis & Henning S. Mortveit

Abstract

Climate change poses significant challenges to agricultural sustainability and food security, which is exacerbated by the increasing frequency and severity of hurricanes. Traditional crop cultivation methods are particularly vulnerable to these climatic disruptions, leading to substantial economic losses and food shortages, particularly in coastal regions. This paper investigates the potential of Hydroponic Crop Cultivation (HCC) as a supplementary agricultural method to enhance resilience of crop production against hurricanes. Using a system dynamics approach, the study evaluates the adoption of HCC units by farmers in hurricane-prone regions, focusing on lettuce production as a representative crop. The model incorporates various factors, including production, demand, revenue generation, and farmer satisfaction, to simulate different hurricane impact scenarios. The findings suggest that HCC adoption can effectively mitigate food deficits and enhance the economic stability of farming communities during hurricanes. This research provides insights that can help guide policymakers and agricultural stakeholders develop robust agricultural systems capable of withstanding the challenges posed by climate change and natural disasters.

Keywords: Climate change, Hydroponic Crop Cultivation (HCC), hurricanes, food security, agricultural resilience, sustainable agriculture.

4.1 Introduction

The increasing frequency and intensity of natural disasters, particularly hurricanes, pose significant threats to agricultural productivity and food security. This challenge is particularly acute in regions reliant on conventional crop cultivation (CCC), where hurricanes can severely disrupt both production and the food import infrastructure (Knutson et al., 2010; Mendelsohn et al., 2012). In response to these vulnerabilities, innovative agricultural techniques such as Hydroponic Crop Cultivation (HCC) are gaining attention (Zee et al., 2024). HCC systems, designed to grow crops in nutrient-rich solutions without soil, offer a promising alternative due to their resilience against environmental stresses. This resilience is evident in HCC's ability to maintain stable crop production despite external climatic disruptions, thereby ensuring a continuous supply of food and income for farmers (Jones, 2005; Lu, 2021; Resh, 2022).

This paper addresses the impact of hurricanes on food production and explores the potential of HCC as a supplementary agricultural method to enhance resilience. By examining the specific interactions between HCC and CCC, we analyze how the adoption of HCC affects local food systems, farmer satisfaction, which is defined in section 4.3.2, and economic stability during hurricane events. The dynamics considered include changes in food production volumes, market prices, and supply chain disruptions. Our study employs a system dynamics approach to simulate scenarios of varying hurricane intensities, from Category 1 to Category 5, based on the Saffir-Simpson Hurricane Wind Scale (Simpson & Riehl, 1981). The model incorporates key variables such as the level of adoption of HCC by local farmers, the quantity of crops produced by HCC units, demand and supply dynamics, pricing fluctuations, and farmer satisfaction levels. Lettuce was chosen as a representative crop due to its widespread cultivation and sensitivity to climate conditions (Gruda, 2009).

Through this analysis, we aim to identify the specific conditions under which HCC adoption can effectively mitigate food deficits and enhance the resilience of local farming communities, thereby stabilizing economic outcomes for farmers even in the face of severe weather events. This research allows agricultural policymakers to visualize options for robust agricultural systems capable of withstanding the challenges posed by climate change and natural disasters, especially hurricanes in coastal communities and small island developing states (Altieri & Nicholls, 2017; IPCC, 2021).

This paper is structured as follows: The introduction section provides a background on the challenges posed by climate change and hurricanes to traditional crop cultivation methods, emphasizing the need for resilient agricultural practices. The literature review explores existing research on the impact of hurricanes on agriculture, the benefits of HCC, and the use of system dynamics modeling in agricultural studies. The methodology section outlines the system dynamics model developed for this study, detailing the variables, assumptions, and scenarios used to simulate the adoption and impact of HCC. The results section presents the findings from the model simulations, highlighting the effects of HCC adoption on food security and farmer satisfaction under five hurricane conditions. The discussion section interprets these results, drawing policy implications and proposing strategies for optimizing HCC adoption policy. Finally, the conclusion summarizes the key insights and suggests directions for future research.

4.2 Literature Review

The impact of climate change on agriculture has been extensively documented, with numerous studies highlighting the increasing vulnerability of conventional farming systems to extreme weather events such as hurricanes. According to IPCC reports, the frequency and intensity of tropical cyclones have risen in recent decades, posing significant threats to agricultural productivity and food security (IPCC, 2021). Traditional agricultural practices, predominantly reliant on predictable weather patterns, are increasingly inadequate for mitigating the adverse effects of these climatic disruptions (Altieri & Nicholls, 2017). Traditional crop cultivation methods are particularly vulnerable to such disruptions, which can include wind damage, flooding, salt water intrusion, as well as bacterial and chemical contamination of irrigation water and soil. These disruptions can lead to significant economic losses across the agricultural sector and food insecurity in regions that are highly dependent on local food crop production. This section explores existing research on the impact of hurricanes on agriculture, the potential of Hydroponic Crop Cultivation (HCC) as a supplementary farming method, and the application of system dynamics modeling in agricultural studies.

4.2.1 Impact of Hurricanes on Agriculture

Numerous studies have documented the adverse effects of hurricanes on agriculture. Hurricanes can cause extensive damage to crops, soil erosion, and infrastructure destruction, leading to reduced agricultural productivity and increased economic strain on farmers (Mendelsohn et al., 2012; Rosenzweig et al., 2014). The frequency and intensity of hurricanes have been rising due to climate change, exacerbating these impacts, particularly in coastal regions that are especially vulnerable to storm surges and wind damage (Strobl, 2012). These regions, such as those in the Caribbean, often experience severe agricultural losses due to the combination of high winds and saltwater intrusion from storm surges, which can contaminate soils and devastate crop productivity for extended periods (Mohan & Strobl, 2017). For instance, in 2004, Hurricane Ivan destroyed 80% of the nutmeg trees in Grenada, significantly affecting both short-term production and long-term recovery of the nutmeg industry (Mohan & Strobl, 2017). As these coastal regions are heavily reliant on agriculture, the compounded effects of hurricanes pose critical challenges to their economic resilience and food security.

4.2.2 Hydroponic Crop Cultivation (HCC)

Hydroponic Crop Cultivation represents a promising alternative to conventional farming, offering a controlled environment that can mitigate the risks posed by adverse weather conditions. Hydroponics involves growing plants in nutrient-rich solutions rather than soil, which allows for precise control over growing conditions and can lead to higher yields and more efficient resource use (Resh, 2012). This method has been shown to increase crop yields, reduce water usage, and minimize the impact of soil-borne diseases (Gruda, 2009). Studies have shown that HCC can produce crops with fewer inputs of water and fertilizers compared to traditional methods, making it a more sustainable option (Jones, 2005; Raviv & Lieth, 2008; Gerlach et al. 2023). Furthermore, several studies have demonstrated the effectiveness of HCC in producing high-quality crops under controlled environments, making it a viable alternative or supplement to conventional farming, especially in regions prone to climatic instability (Al-Kodmany, 2018). Additionally, HCC systems can be set up indoors or in greenhouses, further protecting crops from environmental hazards such as hurricanes.

4.2.3 System Dynamics Modeling in Agriculture

System dynamics modeling has been widely used in agricultural research to simulate and analyze complex interactions within agricultural systems. This approach allows researchers to evaluate the impacts of various factors, such as climate change, economic policies, and technological innovations, on agricultural outcomes. System dynamics models can incorporate feedback loops, delays, and nonlinear relationships, providing a comprehensive tool for understanding the dynamic behavior of agricultural systems over time (Forrester, 1961). In the context of this study, system dynamics modeling is employed to assess the adoption of HCC units by farmers and their potential to enhance resilience against hurricane-induced disruptions. More recent studies have utilized system dynamics to model the interactions between agricultural practices, market forces, and environmental variables. For example, Sterman et al. (2012) developed a model to assess the impact of climate change on agricultural production and food prices, providing valuable insights into the resilience of different farming systems.

4.2.4 Adoption of Alternative Farming Methods

Research on the adoption of HCC in hurricane-prone areas is relatively nascent. Previous studies have primarily focused on the technical and economic feasibility of HCC systems. For instance, Nguyen et al. (2019) examined the cost-effectiveness of HCC compared to traditional farming methods and found that, despite higher initial setup costs, HCC systems offer significant long-term benefits in terms of yield stability and resource efficiency. Similarly, HCC's potential to enhance food security during adverse weather conditions has been highlighted by recent case studies in the Caribbean and Southeast Asia, regions frequently affected by hurricanes (Thompson et al., 2020).

The adoption of innovative farming methods like HCC is influenced by several factors, including economic incentives, perceived benefits, and access to technology (Orr, 2003). Studies on technology adoption in agriculture have highlighted the importance of financial support, knowledge dissemination, and infrastructure development in facilitating the uptake of new practices (Feder et al., 1985; Van den Ban, 2004). In regions prone to hurricanes, the adoption of resilient farming methods can significantly enhance food security and economic stability for farmers (Lin, 2011).

This study builds on the existing literature by integrating system dynamics modeling with HCC adoption strategies to assess the resilience of agricultural systems in hurricane-prone regions. By simulating various hurricane scenarios, this research aims to quantify the benefits of HCC in maintaining food security and farmer satisfaction. The findings contribute to a growing body of knowledge on sustainable agriculture and offer practical insights for policymakers and stakeholders in enhancing agricultural resilience through innovative practices.

4.3 Methodology

This study employs a system dynamics approach to model the adoption and impact of Hydroponic Crop Cultivation (HCC) in regions susceptible to hurricanes. The methodology involves several key components: defining the system's variables, establishing relationships between these variables, and simulating various hurricane scenarios to assess the performance of HCC units.

4.3.1 System Description

The system under consideration includes multiple stakeholders and components, which is illustrated in Figure 21. It shows the key components and relationships in the system dynamics model, including food import infrastructure, market transactions, and the roles of farmers with and without HCC units.

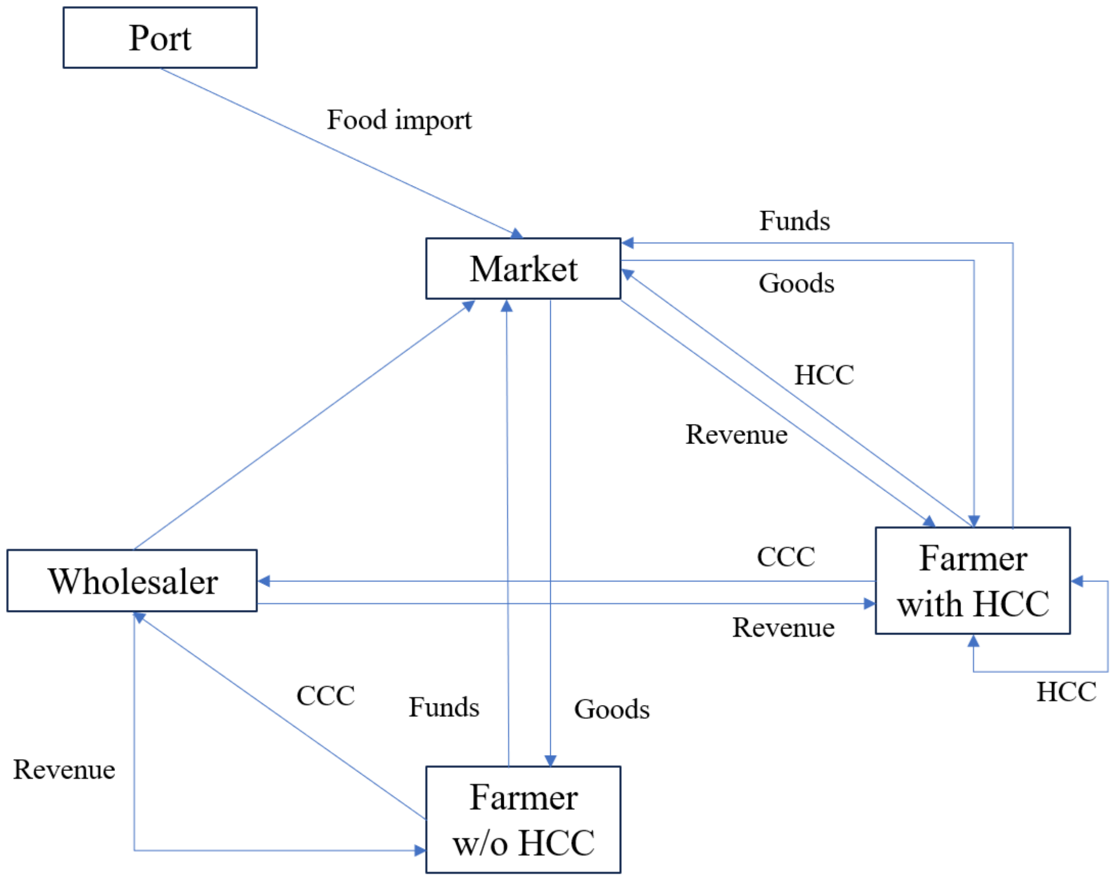

Figure 21. System dynamics model of HCC and CCC interactions.

1) **Port (Food Import Infrastructure):** Handles the importation of food into the region.
2) **Market:** A place where farmers get funds from selling lettuce produced by HCC units and buy goods.
3) **Wholesaler:** It offers a guaranteed prices for all the farmers' CCC produce. Farmers sell food produced by CCC to wholesalers to obtain revenue. However, because of its higher quality, farmers can get a higher price for HCC produce in the market.
4) **Farmers with HCC:** Farmers who adopt HCC units, sell food produced by CCC to wholesalers, grow lettuce in HCC units, consume part of the lettuce, and sell the surplus in the market to obtain revenue.
5) **Farmers without HCC:** Farmers who only engage in CCC and sell their produce to wholesalers, using the revenue to buy food from the market.

4.3.2 Key Variables and Symbols

The model uses several key variables, defined as Tables 13, 14 and 15:

Table 13. Variables and symbols.

Symbol	Description
s	Hurricane category.
Q_L	The quantity of lettuce produced by single HCC unit.
d_L	The demand of lettuce per farmer.
D	The total demand of food (except lettuce) per farmer.
N	The total number of farmers.
α	HCC adoption levels.

When no hurricane exists:

Table 14. Variables and symbols for no hurricane scenario.

Symbol	Description
Q_c	The average quantity of food produced by CCC per farmer.
P_L	The selling price of lettuce when no hurricane exists.
$\bar{P}$	The average price of food (except lettuce) for a farmer when no hurricane exists.
I	The quantity of food imported by import infrastructure when no hurricane exists.

When hurricane category *S* exists:

Table 15. Variables and symbols for hurricane scenario.

Symbol	Description
r_s	The ratio of food produced by CCC which was damaged by hurricane category *s*, compared to the total amount of food.
$P_{c,s}$	The average selling price of food produced by CCC when hurricane category *s* exists.
$P_{L,s}$	The selling price of lettuce produced by HCC when hurricane category *s* exists.
$\bar{P}_s$	The average price of food (except lettuce) for a farmer when hurricane category *s* exists.
R_s	The loss rate of food imports when hurricane category *s* exists.

At this stage, we assume all farmers are homogeneous and each farmer who decides to adopt an HCC unit will only have one HCC unit (Quach et al., 2021; Boland et al., 2022). We also introduce crucial assumptions for this study:

Assumption 1: The production of HCC units is not affected by hurricanes. This assumption highlights the benefit of HCC, as it allows continuous crop production under controlled conditions, unaffected by external climatic disruptions such as hurricanes. This resilience is a significant advantage over CCC, which is highly susceptible to hurricane damage.

Assumption 2: Farmers' primary goal is to meet their own food needs first. They cannot sacrifice their own food needs to sell more produce (lettuce) for profit. This ensures that farmers prioritize their subsistence before engaging in market activities. While it is true that farmers could sacrifice their own food needs to sell more produce and use the income to purchase other food items, this model does not account for that option because it is not relevant to the key point of our intended illustration, which is the contribution of HCC produce to food security for farmers and the local food system.

Farmers get a sense of satisfaction by acquiring food to meet their daily needs, so we define satisfaction as the ratio between farmers' total income from farming and expenditure on food. For a local farmer without HCC adopted, they obtain revenue only from selling food produced by CCC to the wholesaler and then purchasing food from the market to fulfill their need. Their satisfaction, denote as SA is equal to:

$$SA = \frac{(1 - r_s) \cdot Q_c \cdot P_{c,s}}{d_L \cdot P_{L,s} + D \cdot \bar{P}_s}$$

Then we denote SA_{Hcc} as the satisfaction of farmers with HCC adopted. Local farmers who adopted HCC units will grow crops in both CCC and HCC, then they can trade food with the Wholesaler and with the general food market deriving satisfaction that is equal to:

$$SA_{Hcc} = \frac{(1 - r_s) \cdot Q_c \cdot P_{c,s} + (Q_L - d_L) \cdot P_{L,s}}{D \cdot \bar{P}_s}$$

Here, we assume the production of lettuce of a single HCC unit can fulfill the need of a farmer. In other words, under the condition of meeting their own needs, they can also sell the surplus lettuce to the market and obtain revenue. Hence, we assume $Q_L > d_L$ in all circumstances.

To persuade farmers to adopt an HCC unit, SA_{Hcc} should be larger than SA. We can also calculate the regional weighted average satisfaction of farmers as:

$$SA_{avg} = SA_{Hcc} \cdot \alpha + SA \cdot (1 - \alpha)$$

When no hurricane exists, we assume that farmers' demand for food is constant. Over the year, people generally consume a certain amount of food. In that way, the suppliers, both importers and food producers, have a sense of how much they need to produce. Hence, total food supply is equal to total food demand:

$$I + Q_c \cdot N = (d_L + D) \cdot N$$

When hurricane category s exists, the import infrastructure will be damaged and food produced by CCC will be reduced due to a corresponding level of damage. In this scenario, the total supply from food import and CCC should be equal to:

$$(1 - R_s) \cdot I + (1 - r_s) \cdot Q_c \cdot N$$

Hence, the food deficit in this scenario should be equal to the difference between the total food demand before the hurricane of category s and the total food supply after hurricane s:

$$(d_L + D) \cdot N - \{(1 - R_s) \cdot I + (1 - r_s) \cdot Q_c \cdot N\}$$

Because some of the farmers decided to adopt HCC units, the total quantity of food available because of HCC adoption should be equal to the sum of lettuce consumed by HCC farmers and other food purchased with the revenue they earned from the extra lettuce they sell to the market.

$$\{d_L + \frac{(Q_L - d_L) \cdot P_{L,s}}{\bar{P}_s}\} \cdot N \cdot \alpha$$

Consequently, the proportion of the food deficit that HCC can be supplemented is equal to the ratio of total quantity of food available because of HCC unit adoption and the food deficit in the scenario of hurricane s.

$$\frac{\{d_L + [(Q_L - d_L) \cdot P_{L,s}]/\bar{P}_s\} \cdot N \cdot \alpha}{(d_L + D) \cdot N - \{(1 - R_s\,) \cdot I + (1 - r_s) \cdot Q_c \cdot N\}}$$

4.4 Results and Discussion

4.4.1 Data Assumptions and Parameters

The model is tested using the following assumptions:

- Hurricanes are classified into five categories with corresponding damage levels to the import infrastructure and conventional farming.
- Total number of farmers: 1000.
- Initial proportion of farmers adopting HCC units: 20%.
- HCC adoption levels: 60%
- Other values are detailed in Table 16.

Table 16. Model testing values.

Symbol	Value
s	1, 2, 3, 4, 5

Symbol	Value
Q_L	400
d_L	150
D	850
N	1000
α	60%
Q_c	400
P_L	2
$\bar{P}$	2
I	600,000
r_s	0.25, 0.3, 0.38, 0.5, 0.62
$P_{c,s}$	0.5, 0.62, 0.75, 0.93, 1.2
$P_{L,s}$	3, 3.4, 4.0, 4.8, 6.0
$\bar{P}_s$	2.5, 2.8, 3.2, 3.8, 4.8
R_s	0.30, 0.35, 0.42, 0.53, 0.65

The results of the system dynamics model provide insights into the potential of HCC to enhance agricultural resilience in hurricane-prone regions. The analysis focused on farmers' satisfaction levels with and without HCC units under various hurricane scenarios and evaluated the proportion of food deficits that HCC can fill. Here, we discuss these findings in detail.

4.4.2 Farmers' Satisfaction Levels

The results shown in Table 17 indicate a clear distinction between the satisfaction levels of farmers who adopt HCC units (SA_{Hcc}) and those who do not (SA) when 60% of farmers adopt HCC. For farmers with HCC units, satisfaction levels remain relatively high across all hurricane categories, ranging from 41.24% to 43.60%. This consistency underscores the resilience of HCC systems, which continue to produce crops regardless of external climatic disruptions, thereby ensuring a stable food supply and income for farmers.

In contrast, farmers relying solely on CCC experience a significant decline in satisfaction as the severity of hurricanes increases. Their satisfaction drops from 5.83% in a Category 1 hurricane to 3.66% in a Category 5 hurricane. This trend reflects the vulnerability of CCC to hurricane damage, which disrupts food production and import infrastructure, leading to higher food prices and reduced availability.

The regional weighted average satisfaction (SA_{avg}) also shows a declining trend with increasing hurricane severity, though the decline is less steep than that of farmers without HCC units. This suggests that while HCC adoption significantly improves overall satisfaction, the benefits are somewhat diluted by the lower satisfaction levels of non-adopting farmers. Nonetheless, the average satisfaction remains above 26%, even in the most severe hurricane scenario, highlighting the positive impact of HCC adoption on regional resilience.

Table 17. Farmers' satisfaction levels under different hurricane categories.

α = *60%*	*s*				
Satisfaction	1	2	3	4	5
SA_{Hcc}	44.35%	43.81%	43.60%	42.91%	41.24%
SA	6.83%	6.01%	5.60%	4.71%	3.66%
SA_{avg}	29.74%	28.71%	28.40%	27.63%	26.21%

4.4.3 Proportion of Deficit Filled by HCC

The model also evaluates the proportion of food deficits filled by HCC units under different hurricane scenarios, which is shown in Figure 22. The findings reveal a decreasing trend as hurricane severity increases. In a Category 1 hurricane, HCC fills approximately 32.14% of the food deficit, whereas in a Category 5 hurricane, this proportion drops to 17.42%. This decline can be attributed to the increasing damage to CCC and import infrastructure with more severe hurricanes, which creates larger deficits that HCC alone cannot fully compensate for.

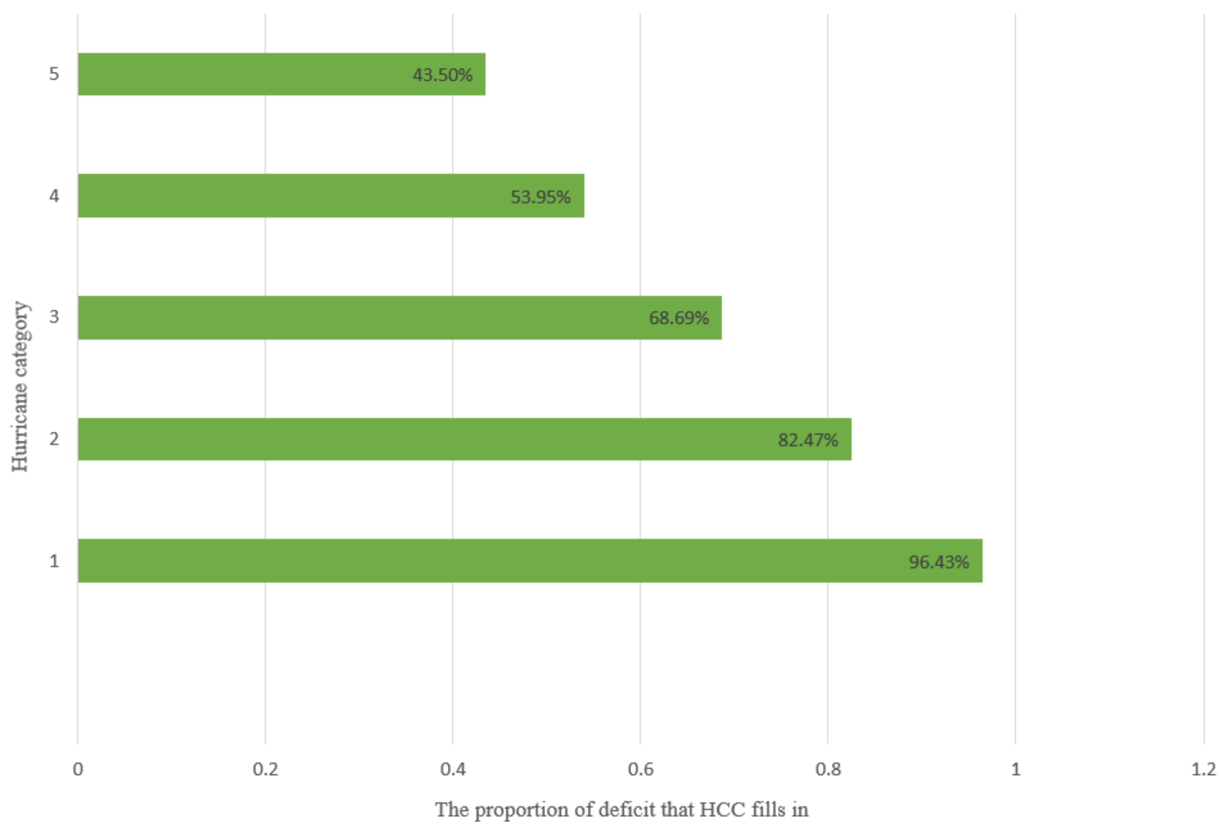

Figure 22. Proportion of food deficit filled by HCC under different hurricane categories.

4.4.4 HCC Adoption Levels

The model was tested under various hurricane scenarios with differing levels of HCC adoption, represented by α, which denotes the percentage of farmers adopting HCC units. The model examines how the adoption of HCC affects both farmers' satisfaction levels and the proportion of food deficits filled by HCC in each scenario. Adoption levels tested were 0%, 30%, 60%, and 90%, across hurricane categories from Category 1 to Category 5.

The regional weighted average satisfaction levels (SA_{avg}) depend heavily on their adoption of HCC units, as shown in Figure 23. The model's results demonstrate a clear upward trend in satisfaction as the percentage of HCC adoption increases.

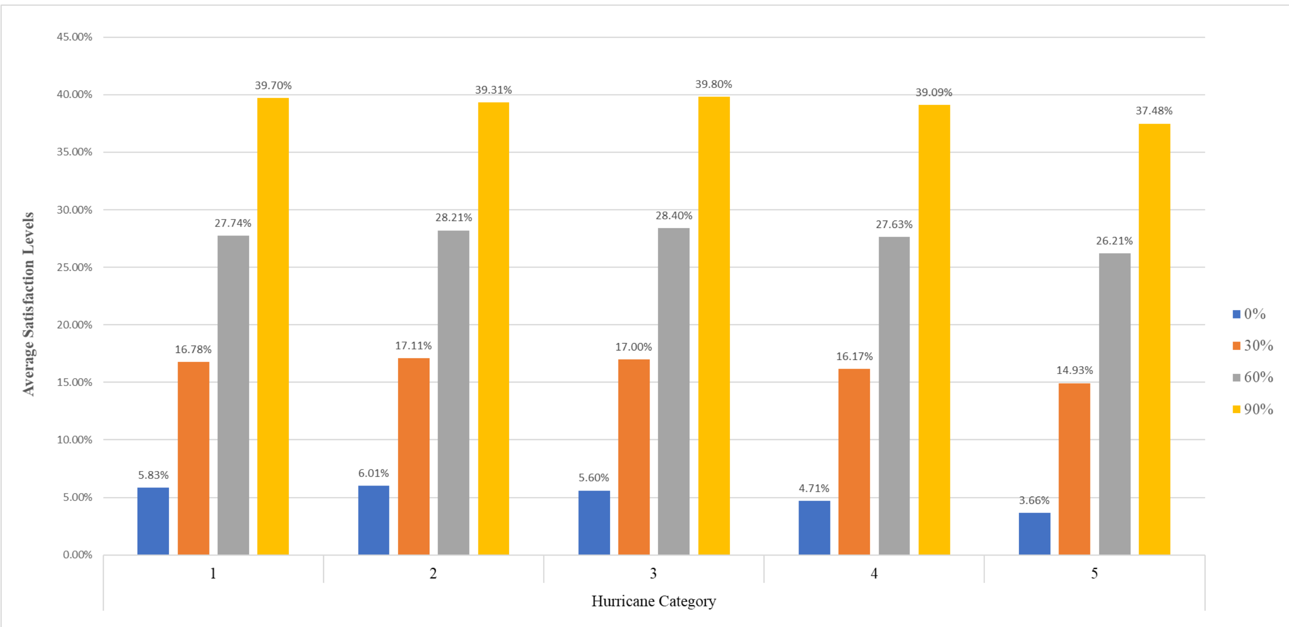

Figure 23 Regional weighted average satisfaction levels under different HCC adoption Levels of five hurricane scenarios.

- **0% Adoption**: When no farmers adopt HCC, satisfaction levels are low across all hurricane categories, ranging from 5.83% in a Category 1 hurricane to a mere 3.66% in a Category 5 hurricane. This reflects the complete reliance on Conventional Crop Cultivation (CCC), which is highly susceptible to damage from hurricanes, resulting in significant crop losses and reduced income.
- **30% Adoption**: With 30% of farmers adopting HCC units, there is a noticeable improvement in satisfaction levels. For a Category 1 hurricane, satisfaction rises to 16.78%, and it remains relatively stable at 14.93% even in the case of a Category 5 hurricane. This shows that even a modest adoption of HCC can provide significant resilience, helping to buffer the effects of moderate hurricanes and preventing satisfaction from dropping too low.
- **60% Adoption**: At 60% adoption, satisfaction levels improve substantially, reaching 27.74% for a Category 1 hurricane and 26.21% for a Category 5 hurricane. This demonstrates that as more farmers adopt HCC, the system becomes more resilient to external shocks,

allowing for better satisfaction even in the face of severe weather events. The steady satisfaction levels across categories highlight the increased stability brought by widespread HCC adoption.

- **90% Adoption**: At 90% adoption, satisfaction levels peak, with 39.70% satisfaction during a Category 1 hurricane and 37.48% during a Category 5 hurricane. This indicates that when the majority of farmers adopt HCC, they can maintain food security and income stability even during the most destructive hurricanes, making the agricultural system highly resilient.

The results underscore the significant positive impact that HCC adoption has on farmers' satisfaction levels. By stabilizing food production and income during hurricane-induced disruptions, HCC adoption helps mitigate the negative impacts on farmers' livelihoods, especially in more severe hurricane scenarios.

Furthermore, the ability of HCC to fill the food deficit created by hurricane-induced damage to CCC is directly related to the level of adoption. The results are listed in Figure 24. As more farmers adopt HCC, the proportion of the deficit filled by HCC increases dramatically, particularly in lower-category hurricanes.

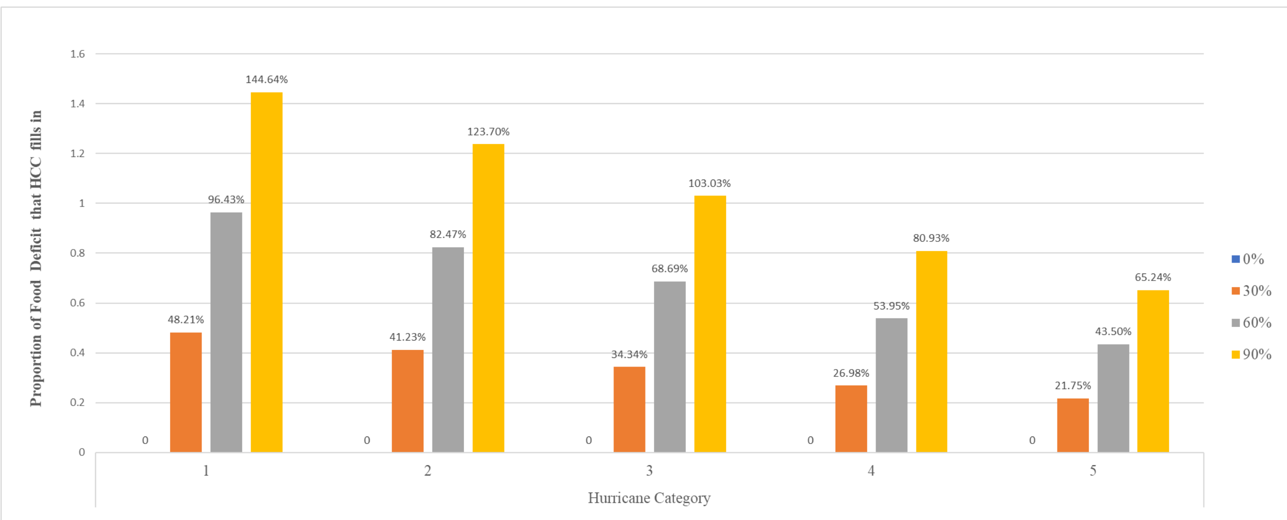

Figure 24 Proportion of food deficit filled by HCC under different HCC adoption levels of five hurricane scenarios.

- **0% Adoption**: With no HCC adoption, the entire food deficit created by hurricanes remains unfilled. This scenario reflects a complete reliance on CCC, which is highly vulnerable to hurricane damage, leading to significant food shortages, especially as hurricane severity increases.
- **30% Adoption**: At 30% adoption, HCC fills 48.21% of the food deficit during a Category 1 hurricane. However, as hurricane severity increases, the proportion of the deficit filled by HCC decreases, dropping to 21.75% in a Category 5 hurricane. This indicates that while HCC helps alleviate food shortages, its effectiveness is reduced as the severity of the hurricane and the corresponding damage to CCC increase.
- **60% Adoption**: With 60% of farmers adopting HCC, the proportion of the food deficit filled by HCC improves significantly. In a Category 1 hurricane, HCC fills 96.43% of the

deficit, almost entirely covering the food needs of the population. Even during a Category 5 hurricane, HCC manages to fill 43.50% of the food deficit. This demonstrates that with a majority of farmers adopting HCC, the system is much more resilient, and food security is largely maintained even in severe hurricane scenarios.

- **90% Adoption**: At 90% adoption, HCC exceeds the deficit in lower-category hurricanes, filling 144.64% of the deficit in a Category 1 hurricane. This surplus highlights the potential of HCC to not only meet local food demands but also generate excess production that could be sold or stored. In a Category 5 hurricane, HCC still fills 65.24% of the food deficit, which is a significant contribution considering the widespread damage caused by such an event.

These results demonstrate that widespread adoption of HCC can significantly reduce the impact of hurricanes on food availability, ensuring that food security is maintained even during the most severe storms.

4.4.5 Policy Implications

The results of this study highlight the crucial role that HCC can play in enhancing agricultural resilience in hurricane-prone regions. Based on the findings, several key policy implications can be drawn to support the wider adoption of HCC and improve food security and economic stability in these areas.

1. **Promote Widespread Adoption of HCC**: The results clearly show that higher levels of HCC adoption led to better outcomes in terms of farmer satisfaction and food security. Policymakers should aim to increase the adoption of HCC units through subsidies, financial incentives, and access to low-interest loans. Governments could also provide direct support for setting up HCC infrastructure, especially in coastal regions that are more vulnerable to hurricanes.
2. **Incentivize Early Adoption**: Targeting policies toward achieving an adoption rate of at least 60% would lead to substantial improvements in both food security and farmer satisfaction. Financial incentives for early adopters, such as tax breaks or grants, could encourage more farmers to switch to HCC and build a resilient agricultural system over time.
3. **Invest in Infrastructure**: In order for HCC to operate effectively, investments must be made in infrastructure such as greenhouses, water supply systems, and nutrient management facilities. These investments will ensure that HCC units can continue operating even in the aftermath of severe hurricanes, further bolstering food security in affected regions.
4. **Develop Training and Support Programs**: To facilitate the transition to HCC, governments and agricultural organizations should offer training programs to educate farmers about the benefits and operation of HCC systems. Providing technical support and demonstration projects would help farmers overcome the challenges of transitioning to new farming methods.
5. **Integrate HCC into National Disaster Preparedness Strategies**: Given the resilience of HCC in the face of hurricanes, policymakers should integrate HCC into broader disaster

preparedness plans. HCC can be a critical component of national food security strategies, ensuring that food supplies are stable even during extreme weather events.

4.4.6 Optimization for Allocation Strategy

The optimization strategy in this study aims to maximize the weighted average satisfaction of farmers while efficiently allocating a limited number of HCC units (*K*). Given budget constraints, this strategy seeks to determine the optimal number of HCC units and their distribution among farmers to maximize the system's overall resilience against hurricanes. The model accounts for variable costs associated with acquiring additional HCC units, allowing the government to manage resources efficiently while maximizing the impact on food security and farmer satisfaction.

The first HCC unit will be acquired for free for those farmers who decide to adopt HCC units as an alternative growing method. If they are willing to hold more than one HCC unit, they have to pay extra money as a cost. If we denote *n* as the number of HCC unit the farmer adopted, the satisfaction of farmers with *n* HCC units adopted can be expressed as below:

$$SA_{Hcc,n} = \frac{(1 - r_s) \cdot Q_c \cdot P_{c,s} + (nQ_L - d_L) \cdot P_{L,s}}{D \cdot \bar{P}_s + \sum_1^n C_n} , \quad n = 1, 2, 3$$

Since the first HCC unit is free for farmers to obtain, $C_1=0$.

If there is a budget for the government to purchase at most *K* HCC units, what is the strategy for the government to assign those units in order to maximize the average weighted satisfaction of farmers.

$$Max \;\; SA_{avg} = SA_{Hcc} \cdot \alpha + SA \cdot (1 - \alpha)$$

$$Max \;\; SA_{HCC} = \sum_{n=1}^{n} \left(SA_{Hcc,n} \cdot X_n \right)$$

$$s.t. \quad \sum_{n=1}^{n} X_n = 1$$

$$N_1 \cdot \sum_{n=1}^{n} (X_n \cdot n) \le K$$

$$0 \le K \le 3 \cdot N_1$$

Nonnegative constraints.

Where X_1, X_2, X_3 represent the proportions of farmers who hold one, two and three HCC units, respectively. We test the model with the adoption level is equal to 60%. So, the number of farmers who adopt HCC units, denote as N_1, is equal to $N_1 = N \cdot \alpha = 1000 \times 60\% = 600$.

Objective:
The primary goal is to maximize the average weighted satisfaction of farmers by optimally assigning HCC units. By focusing on maximizing food security and stability, the strategy seeks to ensure that the allocation of HCC units will support food availability during hurricane disruptions while also providing economic benefits to farmers.

1. **Budgetary Constraints**
   The total number of HCC units, represented as *K*, is limited by a pre-defined budget. This constraint requires the model to operate within financially feasible bounds. The budgetary limit affects how many units can be distributed, directly influencing the scale and speed at which HCC adoption can mitigate food shortages during hurricanes.
2. **Marginal Costs for Additional Units**
   The strategy assumes that the initial HCC unit is provided at minimal or no cost to incentivize adoption. However, farmers who adopt a second or third HCC unit incur marginal costs C_2 and C_3, respectively, reflecting the additional investment required to expand HCC capacity. These marginal costs discourage over-reliance on HCC by any single farmer, promoting broader adoption across the community.
3. **Nonnegative Constraints**
   Constraints ensure realistic satisfaction outcomes by keeping satisfaction values nonnegative and below 100%. The satisfaction of farmers adopting HCC must surpass that of non-adopting farmers, thereby maintaining a meaningful incentive for HCC adoption. This constraint reinforces the strategy's goal of promoting equitable and efficient HCC distribution across the farming community.
4. **Resource Allocation Model**
   The model utilizes a satisfaction function to balance the impact of limited HCC units. Farmers' satisfaction is measured as a ratio of total income from farming to food expenditure. Weighted average satisfaction SA_{avg} depends heavily on HCC adoption rates and the satisfaction improvement attributed to HCC in different hurricane scenarios.

To prioritize the popularization of HCC units so that they help more farmers buffer the effect of hurricane, we encourage the decision maker to set proper values of C_2 and C_3 so that the marginal satisfaction of farmers with multiple HCC units is decreasing. That is,

$$SA_{Hcc,2} \leq 2 \cdot SA_{Hcc,1} \quad and \quad SA_{Hcc,3} \leq \frac{3}{2} SA_{Hcc,2}$$

Thus,

$$C_2 \geq 355 \ \ and \ \ C_3 \geq \frac{2125 + C_2}{21}$$

Sensitivity of Satisfaction to Budget Constraints

Now we know that *K* ranges from 0 to 1800, we would like to discuss the optimal allocation strategies if C_2 and C_3 are assumed to be fixed as 400 and 600. If we test the model by adding 100 to the total number of HCC units each time, the optimal allocation strategies are shown in Table 18.

Table 18 Optimal allocation strategies with C2 and C3 are fixed

C_1	C_2	C_3	K	X_1	X_2	X_3	SA_{HCC}
0	400	600	0	0.00	0.00	0.00	0.000
0	400	600	100	0.17	0.00	0.00	0.072
0	400	600	200	0.33	0.00	0.00	0.140
0	400	600	300	0.50	0.00	0.00	0.212
0	400	600	400	0.67	0.00	0.00	0.284
0	400	600	500	0.83	0.00	0.00	0.352
0	400	600	600	1.00	0.00	0.00	0.424
0	400	600	700	0.83	0.17	0.00	0.493
0	400	600	800	0.67	0.33	0.00	0.558
0	400	600	900	0.50	0.50	0.00	0.628
0	**400**	**600**	**1000**	**0.33**	**0.67**	**0.00**	**0.697**
0	400	600	1100	0.17	0.83	0.00	0.762
0	400	600	1200	0.00	1.00	0.00	0.832
0	400	600	1300	0.00	0.83	0.17	0.870
0	400	600	1400	0.00	0.67	0.33	0.906
0	400	600	1500	0.00	0.50	0.50	0.944
0	400	600	1600	0.00	0.33	0.67	0.982
0	400	600	1700	0.00	0.17	0.83	1.018
0	400	600	1800	0.00	0.00	1.00	1.056

Table 18 presents optimal allocation strategies for HCC units under fixed marginal costs (C_2 = 400 and C_3 = 600) and varying budget constraints (*K*). Here is an example of explanation for Table 8. When *K* is equal to 1000, 33% of farmers hold only one HCC unit and 67% of farmers hold two HCC units. No farmers hold three HCC units. As the total number of HCC units (*K*) increases, the proportion of farmers who can adopt one, two, or three HCC units also rises, with a maximum satisfaction level observed when *K* reaches 1800. The table reveals a progression in allocation where initial HCC units are distributed to achieve broad base coverage (one unit per farmer), then expands to allow a subset of farmers to adopt two units, and finally a few to adopt three units. This tiered distribution strategy indicates a diminishing marginal benefit in satisfaction when moving from one to multiple HCC units, suggesting that resources are more effectively used by maximizing single-unit distribution before expanding additional units to select farmers.

The table's progression emphasizes that, at lower budget levels, satisfaction is maximized by providing single units broadly across farmers rather than concentrating multiple units among fewer adopters. When K is sufficient to cover 1800 units, the strategy allows a more diversified allocation where three-unit adoption becomes feasible, achieving the highest satisfaction levels. This suggests that policymakers could enhance system-wide resilience by first aiming to distribute single HCC units as widely as possible and gradually expanding as budget allows.

Figure 25 depicts the relationship between budget constraints (K) and satisfaction levels of farmers adopting HCC units, with a polynomial trendline illustrating the satisfaction's growth pattern. The trendline suggests that satisfaction increases significantly with each increase in K up to a certain point, after which the rate of increase begins to taper. This non-linear growth highlights diminishing returns on satisfaction as K grows, reinforcing the strategy in Table 8 of initially prioritizing widespread single-unit adoption.

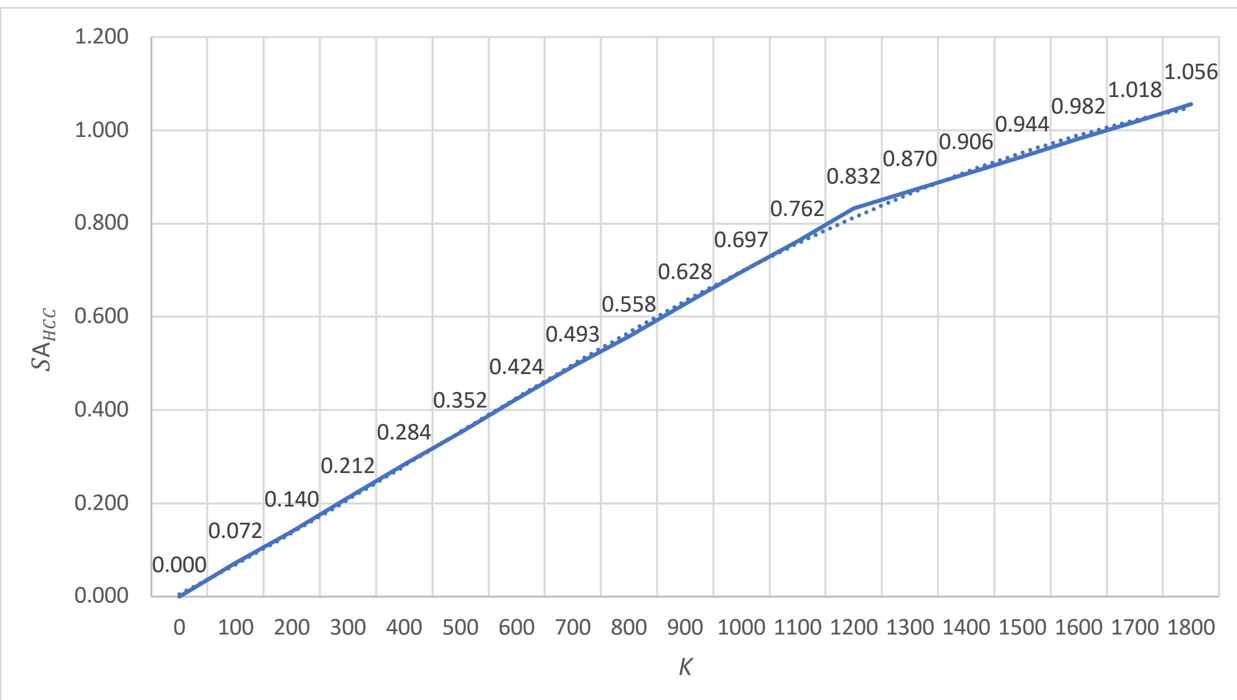

Figure 25 Satisfaction of farmers with HCC adopted (SAHCC) by variations in budget constraints (K)

The trendline's equation below provides a predictive model for satisfaction outcomes at different budget levels, aiding policymakers in estimating the impact of budget adjustments on satisfaction. The polynomial shape of the trendline implies that incremental increases in budget have a substantial effect on satisfaction initially but gradually yield smaller improvements, suggesting that once a core level of adoption is achieved, the focus should shift to system optimization rather than mere expansion.

Trendline equation:

$$SA_{HCC} = 4\mathrm{E}-06\mathrm{K}^4 - 0.0002\mathrm{K}^3 + 0.0033\mathrm{K}^2 + 0.0557\mathrm{K} - 0.0538$$

The insights from Table 18 and Figure 25 underscore the importance of an equitable distribution of HCC units to maximize collective resilience. Policymakers are advised to focus initial resources on reaching a broad base of adoption, prioritizing one unit per farmer where budget constraints are tight. As the budget allows, incremental expansions can allow multiple units for select farmers to further bolster resilience. This approach ensures that satisfaction and resilience benefits are distributed across the farming community, rather than concentrated among a smaller group, enhancing overall food security and economic stability in hurricane-prone regions.

Sensitivity of Satisfaction to Marginal Costs

Next, we test the model when K is fixed as 1500, C_2 ranges from 400±10% and C_3 ranges from 600±10%. Figure 26 plot illustrate how farmer satisfaction levels vary in response to changes in marginal costs for additional HCC units under a fixed budget constraint. It shows that as C_2 and C_3 increase, satisfaction levels generally decrease. This trend is due to the reduced affordability of adopting multiple HCC units, which discourages farmers from acquiring additional units beyond the initial one. Thus, higher marginal costs create a barrier to widespread HCC adoption, resulting in lower overall satisfaction levels among farmers.

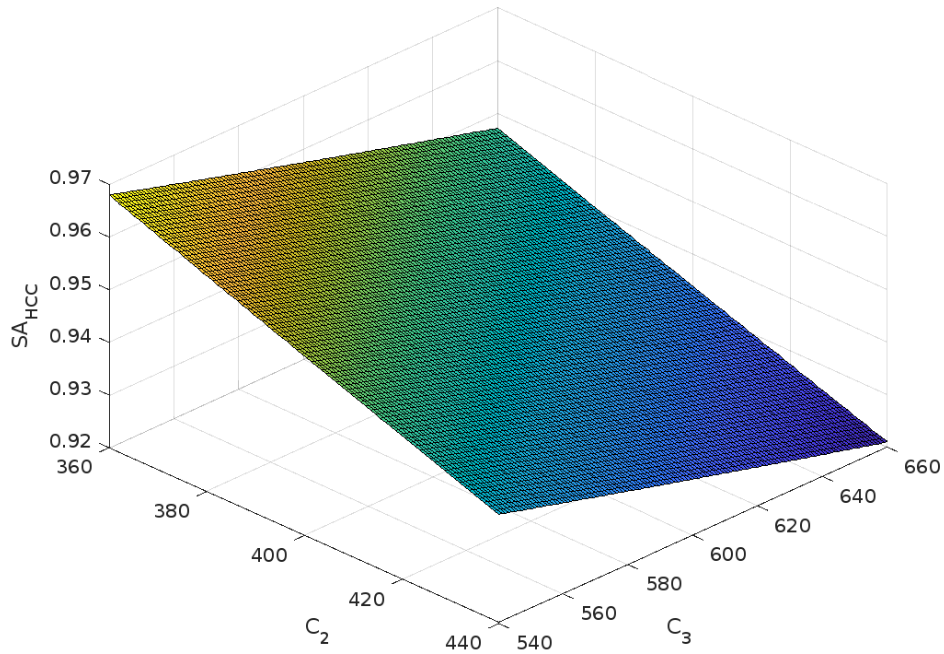

Figure 26 Surface plot of satisfaction levels as influenced by variations in C_2 and C_3.

Figure 25 also reveals that optimal policy should balance adoption incentives with budgetary limits. High C_2 and C_3 values lower satisfaction by limiting the financial feasibility of adopting multiple HCC units, which could reduce the resilience of the farming system. Conversely, if C_2 and C_3 are too low, they may result in excessive concentration of units among a smaller group of farmers. Policymakers are advised to use this analysis to fine-tune marginal cost settings, ensuring that the allocation promotes widespread adoption, optimizes satisfaction, and improves resilience without exceeding budgetary constraints.

4.5 Conclusion and Future Research

This study analyzes the potential of Hydroponic Crop Cultivation (HCC) to enhance agricultural resilience in hurricane-prone regions. By employing a system dynamics approach, we modeled the interactions between HCC and Conventional Crop Cultivation (CCC) under various hurricane scenarios, focusing on factors such as food production, market behavior, pricing, and farmer satisfaction. Our findings highlight the significant benefits of adopting HCC to mitigate the adverse impacts of hurricanes and ensure food security and economic stability for farming communities.

One of the key findings is the enhanced resilience that HCC systems provide. HCC units produce crops in controlled environments, protecting them from external climatic disruptions such as hurricanes. This capacity to maintain stable food production ensures a continuous supply of food and income for farmers even when hurricanes severely disrupt CCC and import infrastructure.

Consequently, HCC systems emerge as a critical supplementary agricultural method that can bolster the resilience of farming operations in hurricane-prone regions.

The study also reveals that farmers who adopt HCC units are likely to experience consistently higher satisfaction levels compared to those relying solely on CCC. Satisfaction levels for HCC adopters remain relatively high (41.24% to 43.60%) across all hurricane categories, while satisfaction for CCC-dependent farmers declines significantly with increasing hurricane severity (from 5.83% in a Category 1 hurricane to 3.66% in a Category 5 hurricane). This underscores the potential of HCC to enhance the well-being and economic stability of farming communities, providing a reliable buffer against the volatility introduced by severe weather events.

Another critical finding is the role of HCC in mitigating food deficits caused by hurricanes. Although the proportion of food deficits filled by HCC decreases with increasing hurricane severity, HCC still makes a significant contribution to food security. For instance, HCC fills approximately 32.14% of the food deficit in a Category 1 hurricane, while in a Category 5 hurricane, this proportion drops to 17.42%. The effectiveness of HCC is more pronounced in lower-category hurricanes, where infrastructure and preparedness are likely better, allowing HCC to have a more substantial impact.

The model also demonstrates that as the level of HCC adoption increases, farmer weighted average satisfaction improves significantly, even during severe weather events. For example, with 90% of farmers adopting HCC, satisfaction levels remain high across all hurricane categories, while reliance on CCC alone leads to a dramatic decline in satisfaction as hurricane severity increases. Additionally, HCC was shown to fill a considerable proportion of the food deficit caused by hurricane-induced disruptions. When adoption reaches 90%, HCC can fill over 65% of the food deficit even during Category 5 hurricanes, emphasizing the system's ability to mitigate the most severe impacts of hurricanes on food security.

Furthermore, the optimization analysis in this study provides insights into the efficient allocation of HCC units under budget constraints. The optimization strategy focuses on maximizing weighted average farmer satisfaction by determining the optimal number and distribution of HCC units. The results show that equitable distribution of HCC units maximizes collective resilience, with the highest satisfaction observed when resources are allocated to provide at least one HCC unit per farmer before expanding additional units to select individuals. This strategy allows the agricultural system to achieve both broad coverage and resilience while efficiently managing budgetary resources.

These findings lead to several important policy implications and recommendations. Policymakers should encourage the adoption of HCC units by providing financial incentives such as subsidies or low-interest loans to offset initial setup costs. Raising awareness about the benefits of HCC through training programs and demonstration projects can further motivate farmers to adopt this resilient farming method. Additionally, investment in necessary infrastructure, such as greenhouse facilities and reliable water and nutrient supply systems, is crucial to support the effective implementation of HCC.

However, there are several limitations that need to be addressed to fully understand the implications of HCC adoption in real-world scenarios:

1. **Cost of HCC Production**
   This study does not take into account the costs associated with setting up and operating HCC units compared to CCC. These costs can affect farmers' willingness to adopt HCC, as the higher initial investment and operational expenses may serve as a barrier to widespread adoption. Furthermore, the cost differences could influence the selling price of HCC produce, which might impact market competitiveness. Future research should incorporate a detailed cost-benefit analysis to assess how economic factors influence the adoption and scaling of HCC.
2. **Higher Yields from HCC**
   HCC units have the potential to produce multiple crops per year due to their ability to operate in controlled environments year-round, unlike CCC, which is typically limited to a single growing season. This study does not fully explore the yield advantages of HCC over CCC, which could result in significantly higher food production from HCC systems. Future models should incorporate this increased yield potential to more accurately capture the full benefits of HCC.
3. **Operational Vulnerabilities**
   While HCC units are resilient to environmental factors, they are still vulnerable to power outages and water supply interruptions that often accompany hurricanes. These disruptions could impede HCC’s ability to produce crops continuously. However, HCC systems can be designed to mitigate these risks through the integration of solar microgrids and rainwater storage systems, ensuring operational continuity during and after hurricanes. Policymakers and planners should consider these backup systems when promoting HCC adoption.
4. **Geographic Specificity and Heterogeneity Among Farmers**
   This study assumes a homogeneous farming population, which may not reflect the diverse characteristics of real-world agricultural systems. Farmers and farms vary in size, access to resources, and susceptibility to hurricane damage. Additionally, geographic factors, such as proximity to the coast, could influence how farms are affected by hurricanes. Future work should explore these variations by incorporating geographic specificity and heterogeneity among farmers into the model. This would provide a more nuanced understanding of how different types of farms and regions may benefit from HCC.

Chapter 5

Portfolio Agriculture: A Model for Resilient Regional Agricultural Planning

Published in Research on World Agricultural Economy. https://doi.org/10.36956/rwae.v5i4.1200

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Abstract

Climate change poses a significant threat to global food security, requiring agriculture and farming livelihoods to adapt to new and unpredictable conditions. Given the sensitivity of agricultural yields to microclimate variations, a locally tailored data-driven approach is essential. Furthermore, limited agricultural resources like water and labor increasingly constrain food production. This research introduces a regional portfolio model to identify optimal crop choices and portfolio compositions based on microclimate variation in temperature and humidity. The model will help farmers evaluate tradeoffs between financial returns and agricultural production risks. The model involves three steps. Firstly, we divided regional agricultural land into farming subunits that each represents a terroir characterized by temperature and humidity. We then use a simulated yield coefficient to assess the effect of microclimate variables on the yield of the different crops in the portfolio of each subunit. Secondly, we optimized farming resource allocation, represented by water and labor, across crops and farming subunits to maximize the yield and associated financial return from farming across the agricultural region. Finally, we developed a resilient agricultural planning model based on the assumed data for regional microclimate and agriculture resources. The resulting resilient agricultural planning model provides valuable insights for farmers to select crop portfolios and allocate resources effectively, thereby maximizing overall profit.

Keywords

Agriculture portfolio; climate change; terroir; climate risk management; agricultural optimization.

5.1 Introduction

Global food security faces unprecedented challenges as climate change continues to disrupt agricultural systems worldwide. With the global population expected to reach nearly 10 billion by 2050, the pressure on agricultural systems to produce sufficient food in a sustainable manner is immense (Godfray et al., 2010; Tilman et al., 2011). Climate change is exacerbating these challenges by altering weather patterns, increasing the frequency of extreme weather events, and shifting growing seasons, all of which have profound effects on agricultural productivity (Wheeler & Von Braun, 2013). The agricultural sector is particularly vulnerable due to its reliance on climatic factors such as temperature, precipitation, and humidity, which directly influence crop growth and yield (Schlenker & Roberts, 2009).

Microclimates, or localized climate conditions near the Earth's surface, play a critical role in agricultural productivity. These microclimates are shaped by a combination of environmental variables including radiation, air and surface temperatures, humidity, wind, and carbon dioxide levels (Behera et al., 2012). The importance of microclimates is underscored by their influence on key ecological processes such as soil respiration, plant regeneration, wildlife habitat selection, and nutrient cycling (Bramer et al., 2018; Rao & Rao, 2016). Understanding and managing these microclimatic factors is essential for optimizing crop yields and ensuring the sustainability of agricultural practices in the face of changing global climate conditions (Challinor et al., 2014; Grass et al., 2019).

Recent studies have highlighted the need for adaptive strategies in agriculture that take into account the variability and complexity of microclimates (Marko et al., 2017; Holzkämper, 2017). These strategies include the adoption of diversified crop portfolios that are resilient to climatic fluctuations, as well as the development of precise, data-driven approaches to farming that leverage high-resolution climate data (Early & Sax, 2011). By tailoring agricultural practices to specific microclimatic conditions, farmers can enhance their resilience to climate change, reduce the risk of crop failure, and improve overall productivity (Burke & Lobell, 2010).

One of the most significant challenges in adapting agricultural systems to climate change is the accurate prediction of how different crops will respond to varying climatic conditions. Traditional crop models often rely on broad, coarse-scale climate data, which can overlook the nuances of local microclimates and lead to less accurate predictions (Khanal & Mishra, 2017; Alkimim et al., 2015). High-resolution microclimate data, on the other hand, allows for more precise modeling of crop suitability and yield, enabling farmers to make better-informed decisions about which crops to plant and when to plant them (Challinor et al., 2018). This data-driven approach is particularly important in regions with significant climatic variability, where small changes in temperature or humidity can have a large impact on crop performance (Lu & Louis, 2021).

In addition to the challenges posed by climate change, the agricultural sector must also contend with the increasing scarcity of vital resources such as water, arable land, and labor (Liu et al., 2023; Chen, 2021). The competition for these resources is intensifying as population growth drives up demand for food, leading to more intensive agricultural practices and greater strain on the environment (Harmel et al., 2020; Meng & Wu, 2021). Efficient resource management is therefore crucial for maintaining agricultural productivity and sustainability. The application of financial portfolio theory to agriculture offers a promising solution to this problem by optimizing the allocation of resources across different crops, balancing the trade-offs between risk and return (Ale et al., 2020).

The concept of portfolio agriculture is based on the principles of diversification, which in the financial world involves spreading investments across a range of assets to minimize risk and maximize returns. In agriculture, this approach involves diversifying crop selection and resource allocation to buffer against the uncertainties of climate change and market fluctuations (Rădulescu et al., 2014). By adopting a portfolio approach, farmers can increase their resilience to adverse conditions, optimize the use of limited resources, and enhance the sustainability of their farming practices (Palash & Bauer, 2017).

This study builds on the principles of portfolio agriculture by developing a regional portfolio model that integrates microclimate data with resource allocation strategies. The model is designed to help farmers make informed decisions about crop selection and resource use, taking into account the specific microclimatic conditions of their land. By dividing agricultural land into subunits characterized by distinct microclimates—referred to as terroirs—the model assesses the impact of temperature and humidity on crop yields and optimizes resource distribution accordingly. The goal is to maximize agricultural output while minimizing risk, thereby contributing to more sustainable and resilient farming practices in the face of climate change. Three steps will be taken to achieve these goals. Firstly, we divide regional farmlands by terroir and measure the effect of microclimate on crops yields by introducing a yield coefficient. Secondly, we optimize farming resource allocation among crop type and farmland parcel by using a portfolio model based on the terroir variables of temperature and humidity. Finally, a numerical experiment is carried out to verify and validate the model.

5.2 Methodology

In this study, we aim to identify portfolios of crop that maximize the profit of farmers in a region based on terroir and the related allocation of crop production resources. The methodology encompasses three key components: terroir, resource allocation theory, and the portfolio agriculture planning model. Terroir involves dividing agricultural land into subunits based on environmental factors such as temperature and humidity, which significantly impact crop yields. Resource allocation theory is used to optimize the distribution of limited agricultural resources like water and labor across different crops and subunits. The portfolio agriculture planning model applies financial portfolio optimization principles to agriculture, allowing farmers to balance the tradeoffs between risk and return when selecting crop portfolios and resource allocations.

5.2.1 Terroir

Terroir, a term rooted in the French tradition of viticulture, broadly encompasses the environmental factors that influence crop growth and quality. Among these factors, temperature and humidity play pivotal roles in determining crop yield. Temperature affects plant metabolism, growth rates, and development cycles, with each crop having an optimal temperature range for maximum productivity. Excessive heat or cold can stress plants, reducing yields or even causing crop failure. Humidity, on the other hand, influences water availability, disease prevalence, and transpiration rates. High humidity can promote fungal diseases, while low humidity can lead to water stress. Together, temperature and humidity create a complex interplay that significantly impacts agricultural output. Understanding and managing these elements of terroir are crucial for optimizing crop yield and ensuring food security in the face of changing climatic conditions.

In this paper, we divide regional agricultural land into farming subunits that each represents a terroir characterized by mean temperature and humidity. We denote all farmlands of a rural household as S and assume that we can divide all farmlands as k distinct farming subunits with different terroir, based on mean temperature and humidity, which essentially affect the yield productivity of different crops. For example, 15 distinguished farming subunits have been divided in Figure 27. For illustrative purposes of this terroir approach, we assume temperature decreases from north to south by 1°C (If the farmland is in the Northern hemisphere, temperature generally increases from North to South) and humidity increases from west to east by 1% for each farming subunit. Hence, if we denote T and H as temperature and humidity, they can be expressed by the following equation for each farming subunit:

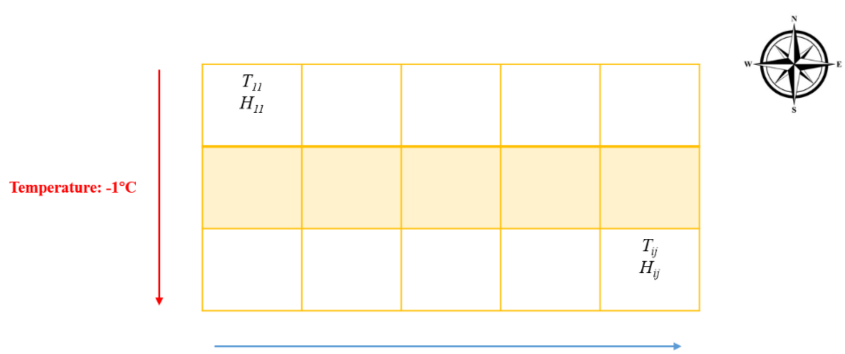

Figure 27 Example of farming subunits

Temperature Equation: $$T_{ij} = T_{11} - (i - 1) \times 1°\text{C} \quad (1)$$

Humidity Equation: $$H_{ij} = H_{11} + (j - 1) \times 1\% \quad (2)$$

Next, we used a simulated yield coefficient to assess the effect of temperature and humidity on the yield of corn, soybeans and cotton for each farming subunit. These common crops are chosen to illustrate the portfolio model, based on data available in the literature. Actual crop yield data would have to be collected to apply the model in practice. Schlenker and Roberts estimated the impact of climate change on crop yields (Schlenker & Roberts, 2008). Table 19 shows the data they collected for temperature with the corresponding log yield of corn, soybeans and cotton.

Table 19 Relation between temperature and crop yield

	Log Yield (bushels/acre)		
Temperature (Celsius)	**Corn**	**Soybeans**	**Cotton**
0	0.002	0.003	-0.025
5	0.001	0.001	0.01
10	-0.003	-0.005	-0.015
15	-0.002	-0.003	0
20	-0.001	-0.002	-0.003
25	0.01	0.01	-0.006
30	0.0015	0.004	0.02
35	-0.02	-0.02	-0.01
40	-0.04	-0.04	-0.04

In this table, a difference of 0.001 indicates approximately a 1% difference in average yield growth. For example, the yield of corn at a temperature of 25 Celsius is 5% higher than that at 40 Celsius, holding all else the same. We did regression analysis to create polynomial trendline equations below to formulate the relationship between temperature and yield of corn, soybeans and cotton.

Corn:

$$Y1 = 2e-08T^5 - 2e-06T^4 + 7e-05T^3 - 0.0009T^2 + 0.0034T \tag{3}$$

Soybeans:

$$Y2 = 2e-08T^5 - 2e-06T^4 + 8e-05T^3 - 0.001T^2 + 0.0038T \tag{4}$$

Cotton:

$$Y3 = 2e-08T^5 - 2e-06T^4 + 8e-05T^3 - 0.0011T^2 + 0.0052T \tag{5}$$

Furthermore, based on the USDA News Releases from 2021 to 2023 and the relative humidity map for Virginia, Table 20 was created to show the average relative humidity of Virginia in August and September from 2021 to 2023 with corresponding yield per acre of corn, soybean and cotton.

Table 20 Relation between average relative humidity and crop yield

Year	Month	Average Relative Humidity (%)	Corn (bushels/arc)	Soybean(bushels/arc)	Cotton(pounds/arc)
2021	August	72	158	45	1045
	September	74	157	43	1100
2022	August	71	160	46	1045
	September	70	162	47	1036
2023	August	75	156	41	1131
	September	76	150	40	1000

We did regression analysis to create polynomial trendline equations below to formulate the relationship between the average relative humidity and the yield per arc of corn, soybeans and cotton.

Corn:

$$y1 = -0.0042H^5 + 1.45H^4 - 201.5H^3 + 13977H^2 - 483816H + 7e+06 \quad (6)$$

Soybeans:

$$y2 = 0.0125H^5 - 4.5417H^4 + 659.9H^3 - 47929H^2 + 2e+06H - 3e+07 \quad (7)$$

Cotton:

$$y3 = -0.4375H^5 + 157.29H^4 - 22615H^3 + 2e+06H^2 - 6e+07H + 8e+08 \quad (8)$$

If we regarded 25 Celsius and 70% average relative humidity as a standard terroir combination, then we introduced yield coefficient β_1, β_2 and β_3 to express the effects of terroir on the yields of corn, soybeans and cotton, respectively. To simplify the model, we use a linear function to sum-up the effects of temperature and humidity on crop yields as follows:

Corn:

$$\beta_1 = \frac{Y1 - 0.01}{0.01} + \frac{y1 - 162}{162} \quad (9)$$

Soybeans:

$$\beta_2 = \frac{Y2 - 0.01}{0.01} + \frac{y2 - 47}{47} \quad (10)$$

Cotton:

$$\beta_3 = \frac{Y3 + 0.006}{0.01} + \frac{y3 - 1036}{1036} \quad (11)$$

5.2.2 Resource Allocation Theory

The portfolio model was originally developed to help investors select asset portfolios that maximize returns or minimize risks in the financial market. The challenge farmers face in selecting the optimal resource allocation among crops can be viewed as a specific application of this investment model. Several studies have utilized the portfolio model to optimize how farmland is allocated among different crops (Lowenberg-DeBoer & López-Pereira, 1990; Rădulescu et al., 2014). Lence applied a standard portfolio model, incorporating additional land constraints, to address the issue of land resource allocation (Lence & Hart, 1997). Nalley employed portfolio theory to select wheat varieties, aiming to minimize risk based on historical yield levels (Nalley & Barkley, 2010). In agricultural production, allocating limited resources is fundamentally similar to how investors manage assets in the financial market. Therefore, optimal resource allocation across different crops is achievable.

5.2.3 Portfolio Agriculture Planning Model

In this research, the portfolio model was used to optimize the distribution of essential agricultural resources, specifically water and labor. This approach allows stakeholders to balance the trade-offs between return and risk across various investment options, with risk being quantified by the variance in returns (Markowitz, 2010). A higher variance indicates greater risk variability and potentially higher investment returns.

We denote all farmlands of a rural household as *S* and assume that we can divide all farmlands into *k* distinct plots with different terroir, represented by temperature and humidity. Terroir affects the yield productivity of different crops. We simply measure this effect as a yield coefficient β.

Assuming that a rural household grows *n* kinds of crops in *k* plots, the net return rate from farming can be calculated as:

$$R = \sum_{s=1}^{s=k} \sum_{m=1}^{m=2} \sum_{i=1}^{i=n} x_{msi}\, r_{mi} \cdot \alpha_s \cdot (1 + \beta_{si}) \quad , \tag{12}$$

$$where \ \sum_{s=1}^{s=k} \sum_{i=1}^{i=n} x_{si} = 1 \tag{13}$$

Where *R* is the total net return rate of farming for this household or farming subunit. All returns in this study are net returns. x_{msi} is the proportion of the agricultural resource *m* (water or labor) invested in crop *i* in farmland *s*. r_{mi} is the net return per unit resource *m* of crop *i*; α_s is the proportion of the total area of farmland s. β_{si} is the yield coefficient for crop *i* in farmland *s*, which is affected by terroir. *m=1, 2. s=1, 2 ,..., k. i=1, 2 ,..., n*

Then the investment risk is:

$$V = \sum_{i=1}^{i=n} \sum_{j=1}^{j=n} x_i x_j \sigma_{ij} \tag{14}$$

Where *V* is the investment risk measured by the dimensionless variance. x_i is the proportion of an agricultural resource invested in crop *i*. x_j is the proportion of an agricultural resource invested in crop *j*. σ_{ij} is the covariance of net return per unit resource between crop *i* and *j*; *i, j=1, 2 ,…, n.*

The covariance of net return per unit resource between two crops is:

$$\sigma_{ij} = E\{[r_i - E(r_i)][r_j - E(r_j)]\} \tag{15}$$

Where r_i is the net return per unit resource of crop i, r_j is the net return per unit resource of crop j. *E* represents the expectation.

To maximize the net return rate of farming under a certain risk level, the objective equation is expressed as follows:

$$Max\ R = \sum_{s=1}^{s=k} \sum_{m=1}^{m=2} \sum_{i=1}^{i=n} x_{msi}\, r_{mi} \cdot \alpha_s \cdot (1 + \beta_{si}) \tag{16}$$

$$s.t.\ V = \sum_{i=1}^{i=n} \sum_{j=1}^{j=n} x_i x_j \sigma_{ij} \leq \gamma \tag{17}$$

$$\sum_{s=1}^{s=k} \sum_{i=1}^{i=n} x_{si} = 1 \tag{18}$$

$$\sum_{s=1}^{s=k} \alpha_s = 1 \tag{19}$$

where *γ* is the actual average risk of faming.

5.3 Results and Discussions

In this section, we perform a numerical experiment to demonstrate the application of the portfolio agriculture planning model. We divide the farmland of a rural farming region into 20 distinct farming subunits or plots with different terroir. Table 21-23 shows the information of area proportion, temperature and humidity for each farming subunits.

Table 21 Area proportion of farming subunits.

	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}
α	0.05	0.03	0.04	0.06	0.04
	S_{21}	S_{22}	S_{23}	S_{24}	S_{25}
α	0.02	0.06	0.04	0.03	0.05
	S_{31}	S_{32}	S_{33}	S_{34}	S_{35}
α	0.03	0.04	0.08	0.03	0.02
	S_{41}	S_{42}	S_{43}	S_{44}	S_{45}
α	0.05	0.07	0.06	0.12	0.08

Temperatures (Celsius) decrease from north to south. We assume the temperature for farming subunits S_{11} is 25 Degree Celsius, then the temperature for other farming subunits can be derivative from the temperature equation as Table 22:

Table 22 Temperature for farming subunits

	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}
T	25	25	25	25	25
	S_{21}	S_{22}	S_{23}	S_{24}	S_{25}
T	24	24	24	24	24
	S_{31}	S_{32}	S_{33}	S_{34}	S_{35}
T	23	23	23	23	23
	S_{41}	S_{42}	S_{43}	S_{44}	S_{45}
T	22	22	22	22	22

Average Relative Humidity (%) are increase from west to east. We assume the average relative humidity for farming subunits S_{11} is 70%, then the average relative humidity for other farming subunits can be derivative from the humidity equation as Table 23:

Table 23 Average relative humidity for farming subunits

	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}
H	70	71	72	73	74
	S_{21}	S_{22}	S_{23}	S_{24}	S_{25}
H	70	71	72	73	74
	S_{31}	S_{32}	S_{33}	S_{34}	S_{35}
H	70	71	72	73	74
	S_{41}	S_{42}	S_{43}	S_{44}	S_{45}
H	70	71	72	73	74

Furthermore, the assumed net return of agriculture resources, water and labor, for the three crops corn, soybean and cotton are shown in the Table 24.

Table 24 Net return of agriculture resources for corn, soybean and cotton

	Water (USD/m^3)	**Labor (USD/day)**
Corn	0.3	66.7
Soybean	0.6	143.3
Cotton	0.19	19.3

These assumed net return data are selected by random number generator, which are used to illustrate the portfolio model, while the actual net return data would have to be collected to apply the model in practice. It should be calculated by the following equation:

$$Net\ return\ =\ price\ \times\ yield\ -\ production\ cost \tag{20}$$

Where production cost includes the cost of labor, machinery, seeds, water, fertilizer, pesticide, and so on.

We assume the original farming strategy for the rural farms can be described in Table 25, which means the farmer distributes water and labor equally to each farming subunit. Terroir has not been considered at this stage.

Table 25 Original farming strategy

Farming Subunit	**Crop**	**Water**	**Labor**
S_{11}	Corn	0.016	0.034
S_{12}	Corn	0.038	0.067
S_{13}	Soybean	0.027	0.036
S_{14}	Soybean	0.012	0.049
S_{15}	Cotton	0.024	0.058
S_{21}	Corn	0.067	0.027
S_{22}	Corn	0.059	0.054
S_{23}	Soybean	0.034	0.029
S_{24}	Soybean	0.063	0.036
S_{25}	Cotton	0.062	0.072
S_{31}	Corn	0.072	0.041
S_{32}	Corn	0.049	0.081
S_{33}	Soybean	0.082	0.034

S_{34}	Soybean	0.028	0.048
S_{35}	Cotton	0.052	0.061
S_{41}	Corn	0.063	0.053
S_{42}	Corn	0.049	0.041
S_{43}	Soybean	0.085	0.038
S_{44}	Soybean	0.049	0.086
S_{45}	Cotton	0.069	0.055

Based on the growing strategy described above, the total net return rate of resources of farming invested in all farmlands for this region is \$4.32 per acre, the actual average risk of farming, denoted by the coefficient γ, is 1.24.

Next, we input the initial data of area proportion, temperatures, average relative humidity, and net return of agriculture resources into the Portfolio Agriculture Planning Model. The aim is to optimize the farming resource allocation across crops and farming subunits and maximize the yield and associated financial return rate from farming across the agricultural region. This model assumes that net return is directly proportional to yield and does not consider the effects of the market in which crop prices would decrease as supply increases, leading to possible diminishing returns. These market effects are outside the scope of this illustrative study and will be pursued in future work. The optimal farming strategy based on these assumptions is shown in Table 26.

Table 26 Optimal farming strategy

Farming Subunit	Crop	Water	Labor
S_{11}	Corn	0.024	0.065
S_{12}	Corn	0.062	0.011
S_{13}	Cotton	0.037	0.063
S_{14}	Soybean	0.049	0.047
S_{15}	Cotton	0.084	0.027
S_{21}	Soybean	0.013	0.086
S_{22}	Corn	0.025	0.067
S_{23}	Soybean	0.064	0.021
S_{24}	Corn	0.071	0.033
S_{25}	Cotton	0.092	0.029
S_{31}	Soybean	0.05	0.066
S_{32}	Corn	0.036	0.071
S_{33}	Soybean	0.028	0.043
S_{34}	Corn	0.049	0.058
S_{35}	Cotton	0.057	0.069
S_{41}	Cotton	0.083	0.027

S_{42}	Corn	0.044	0.039
S_{43}	Soybean	0.039	0.047
S_{44}	Soybean	0.042	0.096
S_{45}	Cotton	0.051	0.035

Based on this strategy, farmers have a clear guidance on growing selected crops in each farming subunits and the optimal agriculture resources (water, labor) input. Considering terroir as essential factors for crop agriculture and applying the Portfolio Agriculture Planning Model (PAPM) to optimize the resource allocation, the total net return rate is increased from \$4.32 per acre to \$5.81 per acre, and the actual average risk of farming, γ, is decreased from 1.24 to 0.89. Consequently, we can conclude that PAPM can help regional farmers to select crop portfolios and make resource allocations based on terroir to maximize overall profit.

5.4 Conclusion and Future Research

This study underscores the potential and efficacy of the Portfolio Agriculture Planning Model in optimizing resource allocation across various crops and farming subunits by incorporating unique terroir characteristics. By integrating microclimate factors such as temperature and humidity, the model has demonstrated a significant enhancement in the total net return rate, increasing from \$4.32 per acre to \$5.81 per acre, while simultaneously reducing the actual average farming risk from 1.24 to 0.89. The reduction of the risk coefficient indicates a significant decrease in agricultural production uncertainty, leading to greater stability in crop yields and economic returns. This enhances farmers' financial resilience, facilitates more predictable investment planning, and reduces exposure to climate and market fluctuations. These improvements highlight the model's ability to provide regional farmers with a robust framework for selecting crop portfolios and allocating resources to maximize overall profitability and sustainability.

The application of the Portfolio Agriculture Planning Model offers a strategic advantage in efficiently managing agricultural resources, addressing critical challenges such as limited farmland, water scarcity, and labor shortages. By tailoring crop choices and resource inputs to specific microclimates, farmers can achieve higher yields and improved economic outcomes, contributing to more resilient and sustainable agricultural practices. The model's ability to optimize resource allocation based on terroir ensures that agricultural practices are both economically viable and environmentally sustainable, supporting broader goals of food security and climate adaptation.

Moreover, this research provides valuable insights for policymakers and agricultural planners aiming to enhance food security and optimize agricultural productivity amidst climatic variability and resource constraints. The model's flexibility allows for the incorporation of additional variables, such as soil characteristics and economic factors, to further refine agricultural planning strategies. This adaptability ensures that the Portfolio Agriculture Planning Model can be tailored to address broader regional and global agricultural challenges, making it a versatile tool for diverse agricultural contexts.

Future research should focus on expanding the model to incorporate real-time data and more granular variables to further improve its predictive accuracy and applicability. Additionally, field trials and practical implementations of the model can provide empirical validation and offer opportunities to refine the model based on real-world feedback. Incorporation of market effects on crop prices would further contextualize the model for real world applications. By continuing to develop and refine the Portfolio Agriculture Planning Model, we can support the agricultural sector in adapting to climate change, optimizing resource use, and ultimately securing a sustainable and resilient food supply for the future.

Chapter 6

Conclusion

In this chapter, the key insights and significant contributions of the dissertation are synthesized, offering a comprehensive overview of the work. Additionally, it identifies potential directions for further research in the field, exploring new opportunities for advancing knowledge.

6.1 Overview of Findings and Contributions

This dissertation examines the potential of Hydroponic Crop Cultivation (HCC) as a climate-resilient agricultural solution in Small Island Developing States (SIDS), where food security is increasingly threatened by extreme weather events and resource constraints. Through empirical experimentation, stochastic optimization, system dynamics modeling, and agricultural portfolio planning, this research constructs a comprehensive framework for evaluating the feasibility, operational efficiency, resilience, and policy implementation of HCC. The findings build upon one another in a structured manner, progressing from technical validation to strategic implementation, ensuring a coherent narrative that informs both scientific inquiry and policymaking. The key contributions of each chapter are outlined below.

Chapter 2 establishes the technical feasibility and farming performance of HCC as an alternative to Conventional Crop Cultivation (CCC). This chapter makes a significant contribution by designing and implementing two distinct hydroponic systems—tray-based and Dutch bucket systems—optimized for efficiency, resilience, and adaptability to local conditions. This chapter also provides empirical evidence that HCC outperforms CCC in terms of yield, water-use efficiency, and climate resilience, making it particularly suitable for resource-constrained and hurricane-prone environments. The findings reveal that HCC can produce up to 6.4 times more yield per cycle than CCC while using up to 8 times less water, highlighting its potential for sustainable agricultural transformation in SIDS. Furthermore, the research underscores the necessity of integrating renewable energy solutions into hydroponic systems, ensuring that HCC remains operationally viable in off-grid settings. By offering a quantitative basis for HCC's advantages over CCC, this chapter provides a critical foundation for subsequent optimization and resilience modeling, ensuring that future analyses are grounded in empirical reality.

Building upon these findings, Chapter 3 addresses the operational challenges of HCC under uncertainty, focusing on risk-aware decision-making for hydroponic food production. While Chapter 2 validates HCC's superior performance, it does not account for the uncertainties in energy supply, demand fluctuations, and disaster-induced disruptions that often affect agricultural production in SIDS. To bridge this gap, Chapter 3 develops a stochastic optimization model that optimally balances production, inventory management, and energy consumption in HCC operations. This chapter's major contribution lies in its ability to translate agronomic performance metrics into a risk-aware decision-making framework, enabling farmers and policymakers to strategically manage hydroponic farming systems under uncertainty. By demonstrating how HCC operations can be optimized despite fluctuating energy costs and uncertain market conditions, Chapter 3 ensures that HCC remains financially and operationally sustainable, reinforcing its long-term viability as an adaptive food production system.

While Chapter 3 focuses on optimizing HCC under uncertain conditions, Chapter 4 shifts the perspective to system-wide agricultural resilience, investigating HCC's role in mitigating the impact of hurricanes on food security and economic stability, particularly in SIDS. This chapter employs system dynamics modeling to assess how different levels of HCC adoption affect food supply stability, farmer income, and market conditions following extreme weather events. A key contribution of this chapter is its ability to quantify the resilience benefits of HCC, demonstrating that higher adoption rates of HCC correlate with reduced post-hurricane food shortages and economic recovery times. The model incorporates various factors, including production, demand, revenue generation, and farmer satisfaction, to simulate different hurricane impact scenarios. The findings suggest that HCC adoption can effectively mitigate food deficits and enhance the economic stability of farming communities during hurricanes. Chapter 4 thus extends the dissertation's contributions from individual farm-level optimization (Chapter 3) to broader food system resilience, offering new insights into how hydroponic farming can function as a shock-absorbing mechanism in disaster-prone agricultural economies.

Finally, Chapter 5 transitions from resilience modeling to strategic agricultural planning, proposing a data-driven portfolio optimization model to guide farmers, policymakers, and investors in making informed decisions about crop selection and resource allocation. While Chapters 2–4 establish HCC's technical feasibility, operational efficiency, and resilience benefits, they do not provide a framework for scaling up climate-smart agriculture in a way that balances profitability, food security, and environmental sustainability. Chapter 5 addresses this gap by developing an agricultural portfolio model that optimally allocates farming resources based on microclimatic conditions, financial risks, and policy constraints. This chapter's major contribution is its ability to integrate climate-responsive decision-making into agricultural investment strategies, ensuring that farmers can build long-term resilience while maintaining economic viability. By offering a scalable framework for agricultural adaptation, Chapter 5 provides practical pathways for integrating HCC into national and regional food security policies, ensuring that the findings of this dissertation can translate into real-world implementation.

Together, these chapters construct a cohesive, evidence-based roadmap for leveraging HCC as a transformative agricultural innovation in climate-vulnerable regions. From empirical validation (Chapter 2) to risk-aware optimization (Chapter 3), resilience modeling (Chapter 4), and strategic implementation (Chapter 5), this dissertation offers a comprehensive, interdisciplinary approach to climate-resilient agriculture. The research findings contribute to both theoretical advancements in sustainable agriculture and practical decision-making frameworks for policymakers, farmers, and development agencies. By bridging science, policy, and real-world applications, this dissertation provides a foundational framework for scaling HCC as a long-term food security solution in SIDS and other climate-vulnerable regions worldwide.

6.2 Suggestions for Future Research

This dissertation has established a comprehensive framework for assessing Hydroponic Crop Cultivation (HCC) as a climate-resilient agricultural innovation in Small Island Developing States (SIDS). While the research presents significant findings in terms of technical feasibility, operational optimization, resilience modeling, and strategic agricultural planning, several areas require further investigation to enhance the applicability, scalability, and impact of HCC systems. Future research should expand upon the methodologies presented in this dissertation by integrating more diverse datasets, improving modeling techniques, and addressing real-world implementation challenges. The following key areas are proposed for future research:

1. Enhancing Hydroponic System Designs for Diverse Agroclimatic Conditions

Chapter 2 developed and evaluated two hydroponic systems—tray-based and Dutch bucket systems—demonstrating their feasibility and efficiency over conventional crop cultivation. However, further research is needed to:

- Expand the scope of crop selection: While this study focused on lettuce, future experiments should examine a wider variety of crops, including high-value cash crops and climate-adaptive staples.
- Evaluate long-term operational efficiency: Current results are based on single-season experiments; long-term studies should assess system durability, nutrient retention, and adaptive design modifications to optimize system longevity.
- Adapt hydroponic systems for resource-scarce environments: Research should explore localized cost-benefit analyses tailored to different SIDS regions, ensuring that hydroponic adoption is financially viable under varying economic conditions

2. Refining Stochastic Optimization Models for Dynamic Resource Management

Chapter 3 introduced a stochastic optimization model to manage production-inventory decisions under uncertainty, incorporating fluctuating energy costs, food demand, and climate-related disruptions. However, additional research is necessary to:

- Integrate real-time data analytics: Future models should incorporate real-time market data, climate forecasts, and sensor-based farm monitoring to enable adaptive decision-making.
- Develop multi-period resilience strategies: Instead of static optimization, models should consider dynamic decision-making frameworks that adjust hydroponic production and inventory levels over multiple disaster cycles.

- Expand risk assessment to include economic and geopolitical variables: Future research should incorporate geopolitical risks, trade policies, and macroeconomic trends affecting food supply chains

3. Strengthening System Dynamics Models for Agricultural Resilience

Chapter 4 employed system dynamics modeling to analyze the role of HCC in post-hurricane agricultural recovery, demonstrating that higher adoption rates of HCC mitigate food shortages and stabilize farmer revenue. Future research should:

- Expand resilience modeling to other extreme climate events: While this study focused on hurricanes, future research should assess HCC's resilience to droughts, flooding, and rising temperatures.
- Incorporate behavioral factors into adoption modeling: The current model assumes rational adoption behavior, but future studies should include farmer decision-making, government interventions, and consumer perceptions to refine adoption scenarios.
- Assess long-term policy interventions: By simulating policy incentives such as subsidies, tax benefits, and infrastructure investments, future studies can offer more detailed policy recommendations for scaling HCC adoption.

4. Advancing Agricultural Portfolio Optimization for Climate-Smart Farming

Chapter 5 proposed an agricultural portfolio planning model that optimized crop selection and resource allocation based on climate, financial, and sustainability constraints. Further research should:

- Extend the model to multi-region applications: Future studies should examine how the portfolio optimization framework can be adapted for different agricultural landscapes, considering regional variations in microclimate, soil conditions, and water availability.
- Validate the model through large-scale pilot studies: Conducting real-world field tests in collaboration with farmers, policymakers, and agribusinesses will help refine the model's predictive accuracy.
- Add market effects on crop prices to further refine the model. Historical data on crop prices and seasonal demand may be used to tune the model so it reflects the expected returns of the portfolio more accurately. This can apply to individual farmers within the region and to the aggregate return to the region.
- Explore the option of profit sharing to minimize the risk of loss to individual farmers within the portfolio region. Rather than maximizing profit across the region and assuming that this represents the average profit for each farming unit within the portfolio, profit sharing would pursue the objective of minimizing the risk of loss to any farming unit within the portfolio region. The line of inquiry would compare the profit maximization and loss

minimization approaches to determine which provides the greater perceived net benefit to farmers.

While the models and experiments developed in this dissertation provide important insights into the design, optimization, and strategic deployment of HCC systems, they are intended to serve as illustrative frameworks rather than universally prescriptive solutions. A number of scientific assumptions and parameter estimations were made throughout the research process—ranging from system performance benchmarks, demand levels, energy prices, climate conditions, and infrastructure availability—that are inherently context-dependent. Accordingly, the real-world application of these findings must be carefully tailored to local socio-economic and environmental conditions. Future studies should explicitly acknowledge and address the conditional nature of model performance, operational outcomes, and policy implications.

For example, the economic and technical viability of HCC systems, as demonstrated in Chapter 2, implicitly assumes stable access to inputs such as clean water, solar energy, labor, and construction materials. These inputs may be variable or constrained in Small Island Developing States (SIDS) due to logistical, climatic, or geopolitical factors. Similarly, the stochastic optimization models presented in Chapter 3, as well as the system dynamics simulations in Chapter 4, are parameterized based on historical data and theoretical estimates of hurricane frequency, energy costs, consumer demand, and adoption rates. However, the effectiveness of these models depends heavily on the accuracy and representativeness of such parameters. For instance, hurricane impacts on supply chains may be nonlinear or clustered, energy availability may be affected by external market shocks, and consumer preferences may shift due to cultural, dietary, or economic factors—all of which could alter the optimal configuration of the HCC system.

Thus, a critical avenue for future research lies in conducting rigorous sensitivity analyses across a broad spectrum of model parameters. These analyses can help identify threshold effects, nonlinearities, and critical leverage points where small changes in inputs produce significant shifts in outcomes. Incorporating Monte Carlo simulations or probabilistic scenario modeling would further enhance the robustness of these findings, enabling researchers and practitioners to better understand the range of possible system behaviors under uncertainty. This would also allow for more nuanced policy guidance, answering questions such as: "Under what conditions does HCC outperform CCC economically?" or "How sensitive is agricultural resilience to shifts in power supply reliability, nutrient availability, or consumer demand volatility?"

Additionally, future work should seek to integrate empirical field data from diverse geographies to validate and calibrate the proposed models. This may include localized cost assessments, yield data, energy consumption metrics, and user behavior studies. Such empirical grounding will enhance model realism and improve the transferability of insights to other regions facing similar food security challenges. Moreover, the development of standardized modeling frameworks and performance metrics will be essential to enable comparative analysis across contexts and support evidence-based investment and policy decisions.

Ultimately, the generalized models and approaches proposed in this dissertation offer a flexible foundation for broader application. However, the operational effectiveness and policy relevance of these models depend on their careful adaptation to local conditions. Recognizing and clearly articulating the assumptions underlying key parameters—and acknowledging the conditional nature of results—will be vital for ensuring the practical impact and scientific credibility of future research in this domain.

6.3 Career Forward

As I approach the completion of my Ph.D., I am at a pivotal stage in shaping the next phase of my career. My doctoral research has equipped me with a strong foundation in system dynamics, risk-aware decision-making, and optimization modeling, particularly in the context of agriculture, energy systems, and supply chain resilience. These skills, combined with my interdisciplinary training in systems and information engineering, position me well for a career that bridges both academia and industry.

At present, I have received offers from several Chinese universities as assistant professor, which aligns with my research expertise and career aspirations. Meanwhile, I am also awaiting decisions from other academic institutions and ICT enterprises which I have applied to. Given my diverse interests and skill set, I am carefully evaluating the opportunities to determine the best fit for my professional growth.

6.4 Publications

This research has resulted in the following publications:

1. Lu, B., Louis, G. & Mortveit, H. (2025). Enhancing Agricultural Resilience to Hurricanes: Evaluating the Adoption and Impact of Hydroponic Crop Cultivation Using System Dynamics. In Review by *Environment, Development and Sustainability*.
2. Lu, B., & Louis, G. (2024). Portfolio Agriculture: A Model for Resilient Regional Agricultural Planning. *Research on World Agricultural Economy*, 5(4), 128–136. https://doi.org/10.36956/rwae.v5i4.1200
3. Lu, B., & Louis, G. (2021). Addressing Schedule Risks in the Process of A Multi-Period Production-Inventory System. In *Proceedings of the International Annual Conference of the American Society for Engineering Management.* (pp. 1-9). American Society for Engineering Management (ASEM).
4. Lu, B., & Louis, G. (2020)."A Literature Review of Hydroponic Crop Cultivation Research". 5th Global Food Security Food Safety and Sustainability. Proceedings of the *5th Global Food Security, Food Safety and Sustainability. Webinar conference*,24-25 August 2020.

5. Gerlach, E. A., Hoang, A., Kamara, S., Longi, A., Sprincis, D. A., Thurmond, E. W., Lu, B. & Louis, G. E. (2023, April). A Floating Farm for Hydroponic Crop Cultivation in Small Island Developing States. In *2023 Systems and Information Engineering Design Symposium (SIEDS)* (pp. 330-334). IEEE.

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