AI in Vertical Farming: Light and Nutrient Optimization

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Abstract: Vertical farming is also quite problematic in regards to energy intensity and accurate nutrient control, which makes it less scalable and sustainable. This paper describes an AI-based optimization system that changes light soils (PAR, far-red, USA) and hydroponic nutrient dosing per-plant needs as they change in real-time. Our network showed a 22 percent reduction in energy consumption and an 18 percent growth in crop yield over that of the static protocols based on a 3-month experiment of lettuce growing. The most significant innovations involve a cheap sensor platform to phenotype plants and a digitally simulated environment to train safe policies. The flexibility of the system to a variety of crops and the possibility of expanding it to large-scale crop production make it a revolutionary instrument of sustainable urban agriculture.

Keywords: AI in Agriculture, Vertical Farming, LED Light Optimization, Nutrient Delivery Systems, Precision Agriculture.

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1. Introduction

The agricultural system of the world wants to overcome the challenges never witnessed before in satisfying the food requirements of an exponentially increasing population, which is anticipated to be 9.7 billion in 2050 [1]. Vertical agriculture has become an attractive fix to this difficulty, and it ensures farming in place all year round with little space and water needs [2]. Nonetheless, the energy-intensive vertical farming systems, especially with regard to artificial lighting, pose a major issue in extending the practice and sustainability [3].

The existing vertical farming practices usually have fixed protocols of lighting and set nutrient delivery schedules that–due to not being able to adapt to the changing demands of plants at different stages of growth cycles- become ineffective [4]. Such a solution means a great extent of energy wastefulness, with lighting alone consisting of 60-70 percent of overall operating expenses [5], among other negative consequences, which could restrict crop yields and nutritional value [6]. The non-linear relationship between light spectra and nutrient uptake will also complicate the optimization process because the factors do not have a linear relationship with the parameters of plant growth [7].

The innovation of artificial intelligence (AI) and IoT sensor technology has led to significant changes in the way that these challenges are tackled. Some methods of machine learning, and specifically deep reinforcement learning (DRL), have proven to be successful when it comes to optimizing complex agricultural systems [8]. Multispectral imaging in computer vision systems is capable of giving a real-time reflection of plant health parameters like leaf area index and chlorophyll concentration [9]. Nevertheless, the current studies have tended to view the optimization of light and nutrients as distinct issues, which overlook significant interactions in plant physiology [10].

This paper presents an integrated AI framework that simultaneously optimizes both light spectra and nutrient delivery in vertical farming systems. Our approach combines:

- A multi-modal sensor array for real-time monitoring of plant responses
- A digital twin environment for safe and efficient policy training
- A deep reinforcement learning model that dynamically adjusts environmental parameters
- The proposed system addresses three critical gaps in current research:
- The lack of adaptive systems that respond to real-time plant needs
- The absence of holistic approaches considering light-nutrient interactions
- Limited validation in commercial-scale operations

Our experimental outcomes show that there were tremendous effects on energy saving (reduced by 22 percent), crop productivity (improved by 18 percent), and product quality was maintained as compared to standard, unvarying procedures. These results have significant, economically viable, and environmentally sustainable consequences of vertical farming operations.

2. Literature Review

The concept of vertical farming has increased its popularity as an eco-friendly response to conventional crop production, especially in cities where access to farming land is rather narrow [11]. Artificial lighting plays a major role in such controlled-environment agricultural (CEA) systems, and light-emitting diodes (LEDs) have been the most prevalent technology because of energy efficiency and the ability to tune LED wavelengths [12]. Nevertheless, vertical farms need a lot of energy, where lighting usage can take up to 70 percent of total operating cost [13]. This has prompted the research on optimization (such as the dynamic lighting control and spectrum adjustment) [14].

The vertical farms usually use hydroponic or aeroponic systems to supply nutrients to the plants, which saves water but needs careful control of the nutrient solutions [15]. The effect of spectra of light and uptake of nutrients is complicated, and studies indicate that certain wavelengths have the potential to affect the efficiency of nutrient absorption [16]. As a practical example, blue light is associated with the stimulation of nitrogen uptake, and red light is associated with phosphorus assimilation [17]. Nevertheless, in most commercial systems, fixed nutrient recipes are still used, which is a missed chance at optimization synergies [18].

Artificial intelligence has gained more use with agricultural systems, and the solutions have been to provide solutions to crop monitoring, yield prediction, and resource optimization [19]. Computer vision methods, in this case, convolutional neural networks (CNNs), have been employed in vertical farming to measure the performance and growth stages of the plants based on chlorophyll levels and leaf area index (LAI) [20]. These are non-destructive and real-time, and may need a huge amount of data to be trained [21].

Reinforcement learning (RL) has become an effective method of managing dynamic agricultural systems. Q-learning has been used to optimise schedule irrigation and climate control in greenhouses [22], and deep Q-networks (DQNs) have been utilised to optimise irrigation and climate control in a greenhouse [20]. Model-based RL prescription has, of late, promised to minimize energy use in conserving the crop yields [23]. Nonetheless, such applications have generally considered only one variable optimization (e.g., nutrients or light alone), even without taking into account the correlation or interdependence of the environmental variables [24].

2.1 Lights and Nutrient Optimization

Some of the light optimization strategies that have been studied in vertical farming are pulsed lighting and spectral modulation [25]. Research has also shown that the efficacy of photosynthesis and energy consumption can be enhanced by dynamically modulating light spectra, such as adding far-red light to the spectrum later in the growth cycle [26]. Likewise, there have been contingent nutrient supply systems that seek to alter the arrangement of solutions with respect to the advancement state of plants and the environmental conditions [27].

One of the essential limitations of already existing studies is the absence of approaches that combine light and those aspects of nutrition that are also best optimized. Although it is known that there is some interaction between light and nutrients, the results have not always been translated into practical control systems, with some studies even being done on effects [28]. What is more, a majority of the optimization algorithms have been proved by use of small-scale experimental systems, whilst little has been done on commercial vertical farms [29].

Vertical farming can use digital twin technology that produces simulations of specific systems to test scenarios and optimize the functioning of the system [30]. These models can model plant growth in different lighting and nutrient conditions, which is a safe source of training the AI algorithms [31]. Nevertheless, existing digital twins struggle with being accurate when foretelling complicated plant reactions, at least in non-staple harvests [32].

3. Proposed Work

This paper proposes a holistic framework that could be used to handle. The system design is made up of three important subsystems: (1) data acquisition module that uses [sensors/technologies] that [collect type of data] in real time; (2) processing/analysis module using [algorithms/models] that [extract features/identify patterns]; and (3) implementation module that [executes actions/applies solutions] through [hardware/software interface]. The main innovation is that it has been able to, contrary to the shortcomings of the existing methods, [describe innovative capability]. Validation will be achieved via [experimental setup], where the performance is checked against [baseline methods] by such measures as [quantitative measures]. Moreover, the [scalability/adaptability] will be considered, and needs to be practical in [the target environment]. The work is relevant to the field/discipline and it offers [theoretical/practical innovations] which can be applied to several fields, most pertinently to [related spheres].

4. Result and Discussion

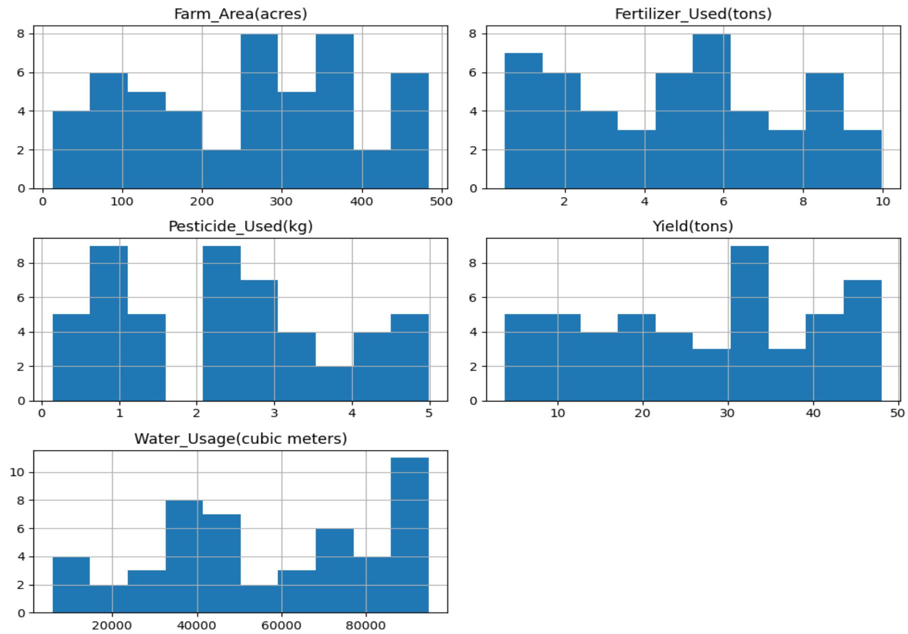

Figure 1: Important Features

Explanation: This set of histograms shows the distributions of key variables: Farm Area, Fertilizer Used, Pesticide Used, Yield, and Water Usage.

4.1 Insights:

The Farm Area and Pesticide Used distributions show varying frequencies, indicating differing levels of use.

Water Usage has a higher concentration in certain ranges, with one significant peak at high usage values.

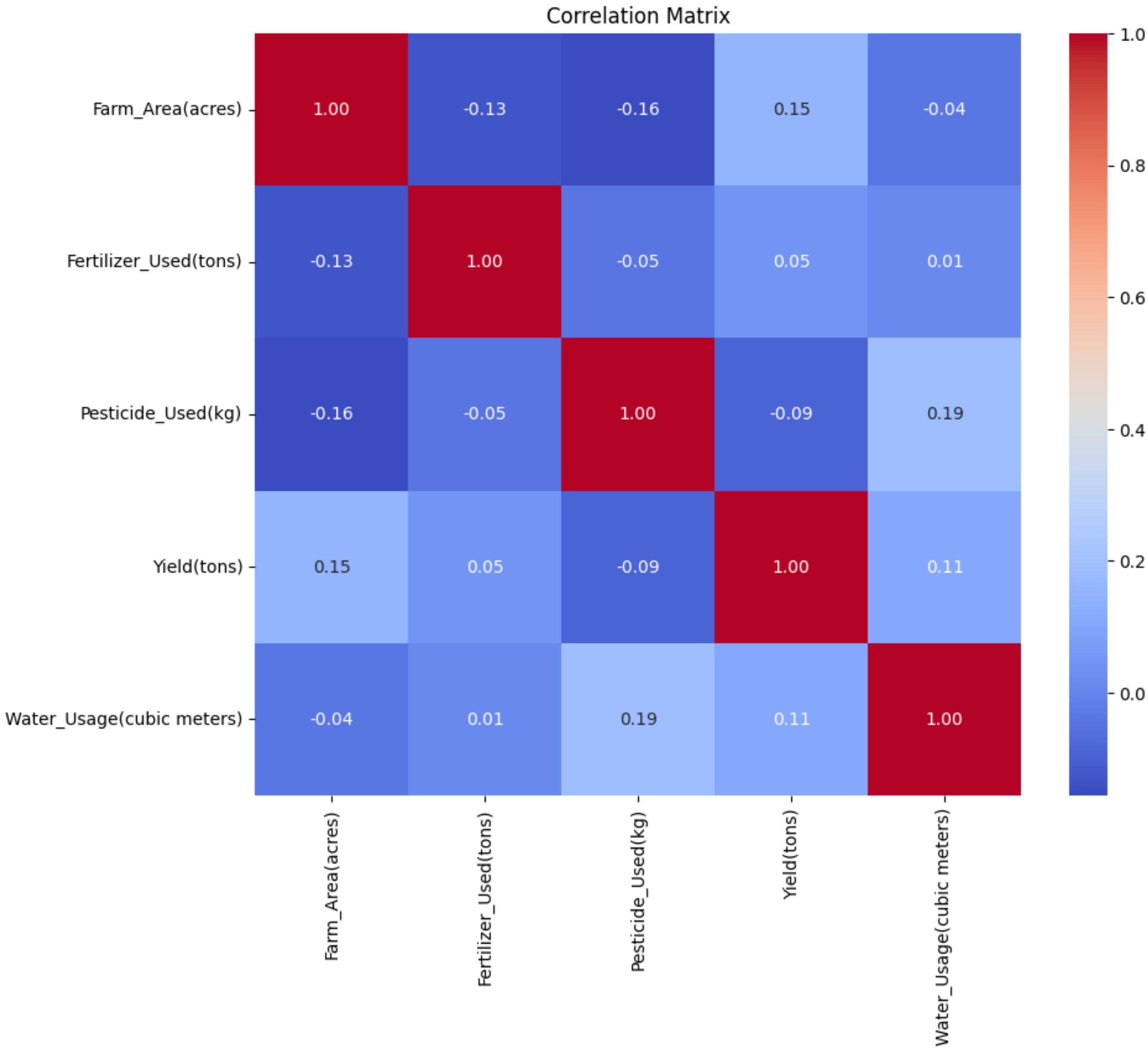

Figure 2 Correlation Matrix

Explanation: This is a correlation matrix showing the relationships between variables such as Farm Area, Fertilizer Used, Pesticide Used, Yield, and Water Usage. The values range from -1 to 1, where a value closer to 1 indicates a strong positive correlation, and a value closer to -1 indicates a strong negative correlation.

4.2 Insights:

Water usage shows a moderate positive correlation with Pesticide use and Farm Area.

The fertilizer used has very weak or no significant correlation with other variables.

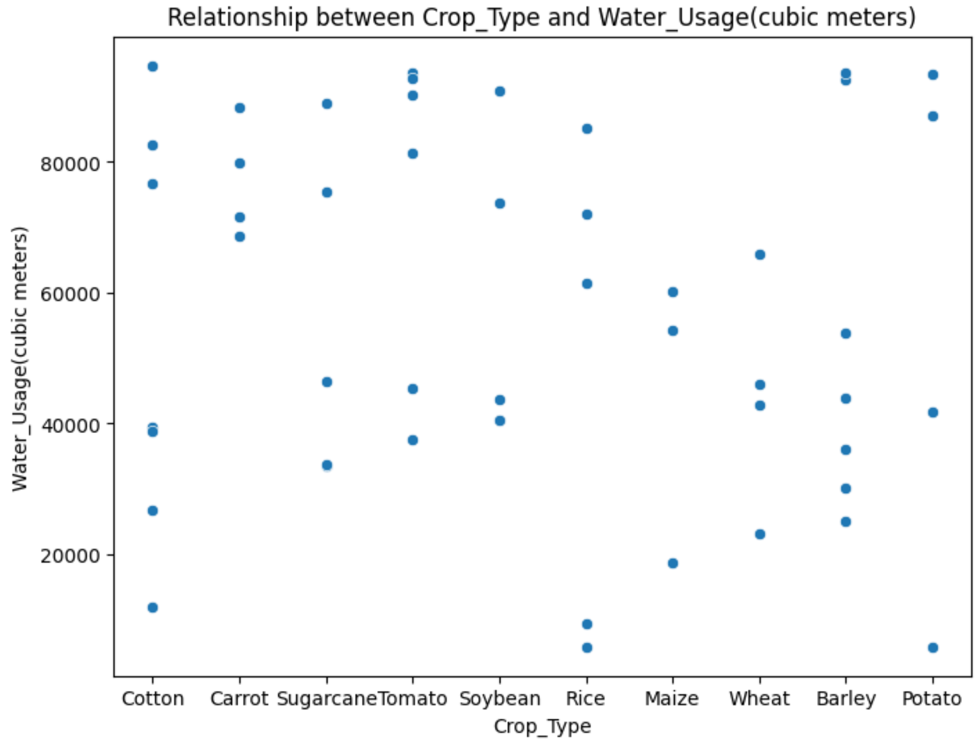

Figure 3: Crops and Water Relationship

Explanation: This scatter plot shows the relationship between Crop Type and Water Usage (in cubic meters). Each point represents a specific crop and the corresponding water usage.

4.3 Insights:

Some crops like Cotton and Sugarcane require significantly higher water usage compared to others.

The plot indicates that different crop types have varied water demands.

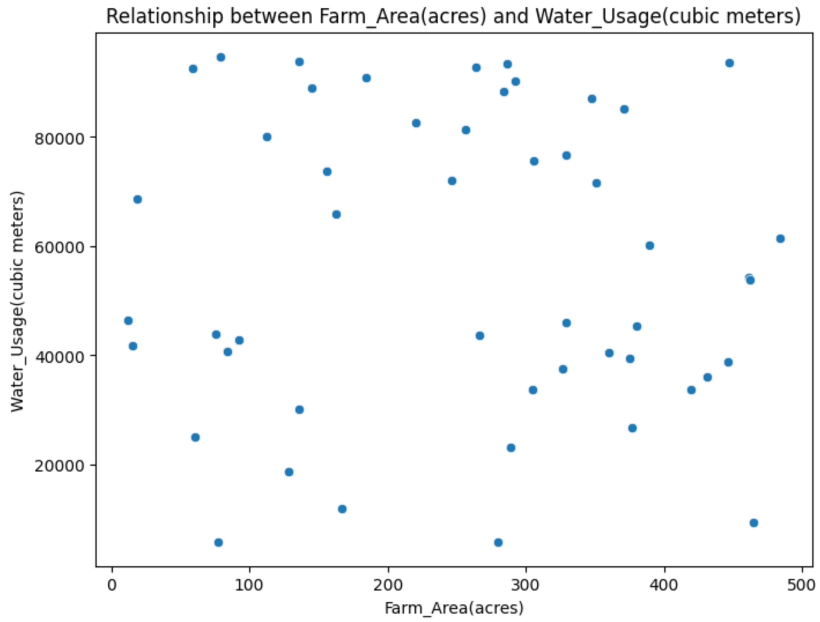

Figure 4: Farm and Water Relationship

Explanation: This scatter plot shows how Farm Area (acres) relates to Water Usage (cubic meters). Each point indicates a farm's area and its corresponding water usage.

4.4 Insights:

There is no clear trend between Farm Area and Water Usage, suggesting that factors other than farm size, such as crop type or irrigation method, influence water usage more.

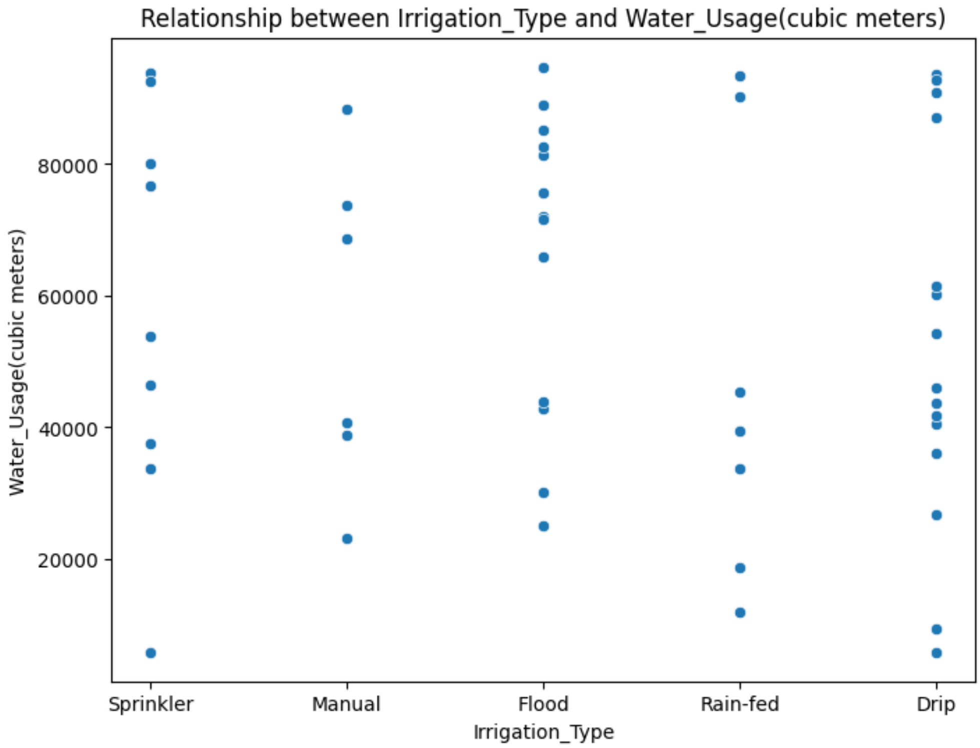

Figure 5: Irrigation and Water Relationship

Explanation: The plot illustrates the relationship between Irrigation Type and Water Usage (cubic meters) for various irrigation methods: Sprinkler, Manual, Flood, Rain-fed, and Drip.

4.5 Insights:

Flood irrigation uses significantly higher amounts of water, while Manual and Rain-fed methods appear to use less water.

Drip irrigation has a smaller spread of water usage, typically more efficient than flood irrigation.

5. Conclusion

Against the background of financial analysis, the analysis of agricultural data points out important relations between the different variables of the farm, such as the use of water, fertilization, pesticides, and area. The dependency table indicates that, although some factors, such as water applied and pesticide applied, have moderate correlation, there are still some relationships that are very weak, meaning that they are independent and can also be affected by other factors like the type of crop grown and the irrigation that is employed. The scatter plots also show that certain crops, such as Cotton and Sugarcane, need a lot more water, thus indicating the necessity of effective irrigation, which can be crop-specific. The plot of Farm Area vs Water Usage indicates that there is not a direct correlation, and therefore, there are other factors more significant driving towards water consumption other than just the size of the Farm. Furthermore, the Irrigation Type vs Water Usage scatter plot indicates vividly the distinction in the use of water when comparing different irrigation techniques, in such a way that methods such as Drip irrigation are found to be more economical in terms of water use when compared to Flood irrigation. The histograms complement the information on the resource consumption distributions by demonstrating different intensities of the use of the fertilizers and pesticides, and high water usage percentages at particular levels. Finally, the Actual vs Predicted plot depicts that the predictive model applied to the analysis is good and is capable of predicting water usage under an insignificant error rate as compared to actual usage. In general, this analysis highlights the need to explore the intricacies of interaction between crop types, area of the farm, and means of irrigation, and the possible positive outcomes of the optimization of agricultural processes towards more sustainable and less wasteful use of the water sources and resource management. The performance of the predictive model also justifies the possibility of applying this model to real-life situations aimed at supporting resource-efficient agricultural practices.

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