Agriculture with Energy Conservation and AI Technology: Analysis of Operational Efficiency of Vertical Farms

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Abstract

The rise of vertical farms offers new opportunities for climate change and agricultural development. Vertical farms use greenhouses and AI technology applications to overcome the agricultural problems of climatic factors and labour shortages. It also leads to the problem of high electricity bills and other operating costs, which affects the operating efficiency. This study aims to analyse the operational efficiency and input-output resource allocation of vertical farms. This study uses a dynamic network DEA model to analyse the first-stage energy efficiency stage, second-stage operating efficiency and overall efficiency of the world's top 8 vertical farms from 2018 to 2022. The research results are as follows: 1. The first-stage input (solar power generation and water-saving equipment) is sufficient, and the intermediate output of the vertical farm (the higher the power generation, the greater the water saving) is prone to economies of scale, and the impact on the vertical farm in the first stage will be Brings positive operational efficiencies to the department. 2. The COVID-19 epidemic has had a significant positive impact on the power generation and energy saving efficiency of the first phase of vertical farms, which means that the energy input and output of vertical farms have been better distributed during the epidemic, and indirectly affected the second phase. stage operational efficiency as well as the overall operational efficiency of the vertical farm. 3. According to the slack variable analysis, in order for vertical farms to achieve the best overall operating efficiency, both input and output factors need to be reallocated and adjusted. Among them, operating costs (power costs) need to be reduced by 38.68%, which is the largest adjustment among all input factor resources. Vertical farms use modern, high-tech artificial intelligence to stabilise crop value supply chains and provide many other functional benefits. However, their operational efficiency is severely hampered by high electricity costs. Therefore, effectively reducing the electricity costs of vertical farm operations will be the key to their success or failure.

Keywords: Vertical farms, Dynamic network DEA model, Artificial intelligence

1 Introduction

The application of AI technology across various industries has led each to thrive. Despite this, the utilization of AI tech within relatively disadvantaged sectors such as agriculture is more uncommon. However, agriculture is a crucial industry for the world's food supply, playing an incredibly significant role. The main innovation of this study lies in analyzing labor and resource-limited agriculture, and exploring how the integration of AI technology can achieve operational efficiency. The goal is to facilitate the optimal allocation of all agricultural inputs and outputs without waste, ultimately helping to stabilize both the global food supply and the agricultural value chain.

Under the wave of global net-zero emission and the development trend of carbon border adjustment mechanisms in Europe and the United States, net zero transformation is an issue of environmental protection. It is closely related to the competitiveness of the agricultural department in charge of food production for all countries and regions. [1] suggested that as a cornerstone of sustaining the ever-growing global population and driving the thriving economy, agriculture assumes a vital role. In other words, how to live in harmony with the natural environment and stabilize food supply is an essential goal of sustainable agricultural development. However, today's agricultural development still faces many issues, such as a change in people's consumption behavior of agricultural products in the post-COVID-19 era and the impact of global climate change on crop yields. [2] found that modern agricultural practices have started the process of agricultural pollution. This process causes the degradation of eco-systems, land, and environment due to the modern-day by-products of agriculture. [3] pointed that long-term fertilization would worsen the quality of agricultural products, yield poor soil ridges, greenhouse gas, and air pollution emissions. An important issue is how to increase the efficiency of food production while at the same time taking into account environmental sustainability.

Recently, vertical farm-related issues are gaining attention in the community [4-7], according to Grand View Research of 2023, the global vertical farming market size was valued at USD 5,894.4 million in 2022 and is expected to expand at

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a compound annual growth rate (CAGR) of 20.1% from 2023 to 2030 [8]. Vertical farming is a refined agricultural breeding technology. It is a production technology that primarily uses environmental control devices to improve issues due to outdoor cultivation being vulnerable to climate factors. Providing a more suitable growing environment for crops can increase yields, enhance output per unit area, and improve quality. Urban land is efficiently used to supply food, where the concept of "proximity growing" is achieved. This reduces the distance of transporting agricultural products to market, thereby saving transportation costs and reducing carbon emissions. Additionally, vertical farming is characterized by the advantage of adaptability to local conditions. [9] pointed that although the problems related to agriculture in various locations (especially in developed and developing countries) seem pretty different, vertical farming can offer solutions to these. However, [10] suggested that in recent years, the development of vertical farming has been affected by the gradual rise in prices of facility materials and energy, along with farmers' willingness to use facilities for cultivation drops due to an increase in investment costs. In other words, factors affecting the operational efficiency of vertical farms are topics worthy of analysis.

The recent integration of AI techniques into agriculture has achieved remarkable results [11-15]. Applying AI systems to agriculture means farmers no longer solely require their personal experience when planting and cultivating crops. They can use big data and scientific analysis to accurately assist field work, thereby reducing costs and saving labor. [16] found that agriculture is a dynamic domain where situations cannot be generalized to suggest a common solution. AI techniques have enabled us to capture the intricate details of each situation and provide a solution that is best fit for that particular problem. Gradually very complex problems are being solved with the development of various AI techniques. The relevant literature indicates that if artificial intelligence (AI) systems can be effectively used and invested as enterprise equipment, such applications may have a positive impact on the financial performance or business performance of enterprises. [17] found that AI adoption in agricultural value chain could increase agriculture income, enhance competitiveness and reduce cost. [18] suggested that there is a positive relationship between entrepreneurial competencies and financial performance of farmers. However, not all agricultural production with AI system inputs can provide the necessary benefits. In Dongs' study on Greenhouse cultivation in 2021 [19], he mentioned that the operating efficiency of some greenhouses is low, resulting in energy and water waste and increasing production costs. Therefore, while discussing vertical farms, the impact of AI smart technology inputs on the operational efficiency of vertical farms is one of the research focuses of this paper.

Based on the above, we suggest that the input and resource allocation of vertical farms may impact their operational efficiency. Therefore, it is essential to explore the optimal allocation combination of input and output in vertical farms to determine the influencing factors that lead to high cost and waste of resources. Based on the above, the dynamic network DEA model proposed by [20] was adopted in this paper to conduct the empirical analysis. The output items of the first stage of operating efficiency include solar power generation benefits and water saving benefits. The input items of market efficiency's second stage include the output of the first stage (intermediate goods), number of employees, operating expenses, and the input cost of AI automation systems. We used the output item of the second stage, EPS, and the net profit as the multi-year carry over to measure the efficiency change in each period. Then, we analyzed the total operating efficiency generated from the multi-year oper-ating profit calculated by the dynamic network DEA model.

2 Literature Review

2.1 Vertical Farm

Crop planting continually impacts the sustainable development of the natural environment. Therefore, how to construct a high-efficiency crop production mode and reduce energy consumption by controlling the growing environment has become an essential issue in agricultural development. [21] pointed that environmental obsessions have been mixed with rising obsession with health as architecture design is concerned. Therefore, it has led to more interest in providing healthy food and incorporating it in the sustainable development project. Hence, it is more important to develop farming methods of crops beneficial to environmental sustainability. [22] pointed that vertical farm could feeding the world in the 21st Century. [23] suggested that vertical farming is a novel plant production system that allows local production of high-quality fruits and vegetables for rapidly growing cities. Vertical farming offers a myriad of opportunities to move from genetic to environmental modification and to produce crops of guaranteed quality and quantity independent of weather, soil conditions, or climate change. In other words, vertical farming has the potential to address these challenges-es and improve the production of high-quality products, such as fresh herbs, fruits, vegetables and flowers [24-25]. Utilizing vertical farming will form a part of resilient food systems and meet daily consumer demands. With the development of vertical farms, their types are becoming more and more diversified. [25] pointed that vertical farming systems can be broadly divided into two categories – those comprising multiple levels of traditional horizontal growing platforms, and those where the crop is grown on a vertical surface. [26] found that typologies of vertical farms present in Europe: i. PFAL (plant factory with artificial light): Vertical farming production system located in devoted space in an industrial building. ii. Container farm: Shipping container equipped with self-contained vertical farming systems. iii. In-store farm: Vertical farming unit located at the place of consumption or purchase (i.e., supermarkets, restaurants) iv. Appliance farm: Plug and play indoor growing system targeted for in-home and office use.

The above classification illustrates that the types of vertical farms are diversified. Furthermore, vertical farms can be sustainable concerning water, fertilizers, and land use. However, there is still room for improvement regarding vertical farms. [27] found that despite the many advantages of vertical farming, the carbon footprint of this technology is 5.6–16.7 times greater than that of other commonly used methods. [28] suggested that the cost-effectiveness, scalability, and environmental sustainability of intensive vertical farming are still uncertain. [29] pointed that he initial investment per square meter of cultivation for a vertical farm can be up to 10 times higher than that of a high-tech greenhouse. These studies echo [23], they pointed that high energy use and investment costs remain a challenge. Therefore, the impact of vertical farm's inputs in energy conservation on operating efficiency is worthy of further discussion.

2.2 Smart Farming

While the world faces the impact of extreme climate, labor and food shortages have become critical issues to be solved in the future development of agriculture. [30] pointed that the new agricultural system must become more productive in output, efficient in operation, resilient to climate change, and sustainable for future generations. Artificial Intelligence (AI) holds promise in addressing the challenges of this new paradigm. In other words, to increase productivity and ensure the quality of agricultural products, promoting artificial intelligence (AI) in agriculture to realize smart agriculture is one method of addressing these issues. [31] found that there has been a significant development in digital agriculture management applications, which has impact-ed information and communication technology (ICT) to deliver benefits for both farmers and consumers, as well as pushed technological solutions into rural settings. This trend could impact global agricultural development. [32] According to Precedence Research's 2023 research report, it showed that he global artificial intelligence in agriculture market size was estimated at USD 1.37 billion in 2022 and it is expected to surpass around USD 11.13 billion by 2032, growing at a Compound Annual Growth Rate of 23.3% from 2023 to 2032. It also showed that precision farming is expected to capture the largest market share over the forecast period. The application of AI artificial intelligence systems may have an essential impact on smart farming. Artificial intelligence (AI) has been applied to agricultural development in several fields. [33] found that what AI can do in Smart Farming include weather, soil, irrigation, unmanned aerial vehicle, pest control, weed control, disease control. As such, AI allows farmers to remotely monitor their crops, soil, fields, and livestock in real-time. It can further analyze collected data and provide precise insights for operational decisions. Moreover, advanced technologies such as autonomous vehicles, robots, and drones can compensate for labor shortages. Despite the substantial benefits AI can bring to agricultural development, the risks it poses must also be considered. [34] discussed the possible risks caused by applying AI to agriculture, including risks relating to interoperability, reliability and relevance of agricultural data, unintended socio-ecological consequences resulting from machine learning models optimized for yields, and safety and security concerns associated with deployment of machine learning platforms at scale. In other words, the actual impact of inputs from the technology intelligence department of vertical farms on output in the end needs to be further explored.

3 Research Methodology

This study explored the the operational efficiency of the energy conservation and environmental protection and AI technology of vertical farms using the dynamic network DEA model proposed by [20]. Furthermore, this study analyzed the total operating efficiency generated from the multi-year operating profit calculated by the two-stage dynamic model. Based on the production operating efficiency of inputs and outputs in the first stage (energy department) and the market operating efficiency of inputs and outputs in the second stage (e.g., AI smart technology department), the total operating efficiency of vertical farms was analyzed as a basis for the operation strategy and resource allocation of vertical farms. This paper primarily studied the energy efficiency stage, market efficiency stage, and overall efficiency performance of the world's top eight vertical farms by revenue from 2018 to 2022.

3.1 Research Design

This study examined the operational efficiency of vertical farms. It primarily analyzed the impact of inputs in energy generation efficiency and AI smart technology on the total operational efficiency of vertical farms. Each department has its own input resources and output; there is a linked operating efficiency relationship (or intermediate goods and services) between the departments, as shown in the Figure 1 below. Where, Link1->2 refers to using part of the output of Department 1 as part of the input of Department 2. Link1->3 and Link2->3 can be under-stood in the same manner.

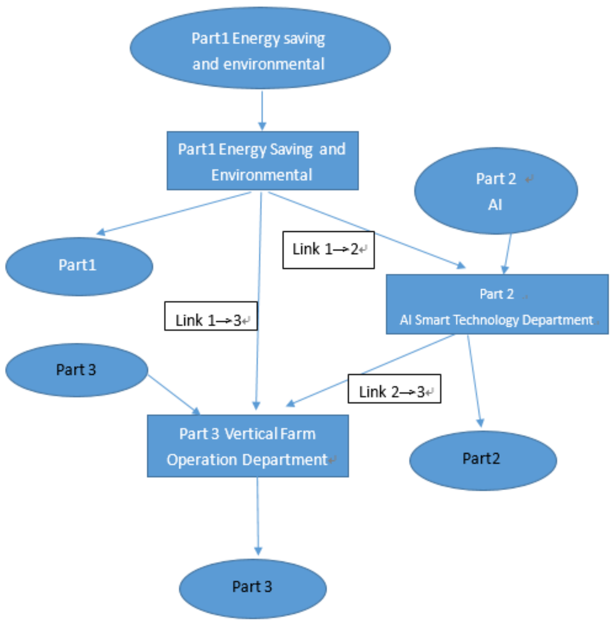

Figure 1. Network DEA model of vertical farms

The above Figure 1 shows that the dynamic network DEA model transforms the production inside the vertical farm into sub-production activities linked and influenced by other departments.

The network model was first proposed by [35] to deal with the situation where there are two interconnected sub-decision-making units within the DMU (decision-maker). The linking relationship is the output produced by one of the sub-decision-making units, which becomes another decision-making unit. The input of the unit is the production efficiency problem of DMU in the so-called intermediate situation. This type of model is called a two-stage network model in the literature. [36] further extended the treatment of the situation with multiple sub-decision-making units in the DMU; [37] distinguished the network architecture into a series system and a parallel system, and proposed the Relational system that combines the two. Network DEA model; [20] established a network model based on the slack-based model (SBM). This model can measure the causes of operational inefficiency of decision-makers and the gap in input-output resource allocation.

Basically, DEA uses a linear or nonlinear mathematical programming method to establish a reference technology frontier based on the production possibility set composed of samples, and then compares it with the technology frontier based on individual samples. The decision-making unit (i.e., the vertical farm in this article) is located at the reference Those on the technological frontier are relatively efficient, otherwise they are relatively inefficient, and the farther away from the frontier, the worse the relative efficiency. However, traditional DEA basically only calculates a single overall relative efficiency value based on the input and output data of the decision-making unit being evaluated [20]. When there are multiple or networked production structures within a decision-making unit, there will be a shortcoming of being unable to understand the efficiency information of specific production activities within it, resulting in limited efficiency measurement results. In order to overcome the above shortcomings of traditional DEA and integrate the advantages of [20] slack-based model (SBM), this study uses the NDEA model proposed by [38] and [39]. In order to provide more complete efficiency assessment information in the production stage and accurately measure the optimal input and output resource allocation of vertical farms.

3.1.1 Sample

This study examines the operational benefits of vertical farming. The input-output and operating benefits of vertical farms under different energy and resource conditions and artificial intelligence technology conditions are analyzed. The top eight vertical farms in the world in terms of revenue are selected as the research objects, and the data comes from Emerge Research Report 2023 [8] as a reference. The data of the top eight vertical farms is shown in the Table 1 below:

Table 1. Features of the world's top 8 vertical farms

DMU	Vertical farm	Country/Revenue	Vertical farm features
D1	AgriCool	France/ US $103 Million	AgriCool uses a closed-loop water system, an aeroponic system to provide optimum growing conditions, and LED lights to regulate light intensity and light spectrum that the strawberries receive. This company utilizes recycled shipping containers, called cooltainers, to produce food with zero pesticides and preservatives.
D2	Bowery Farming	USA/ US $83.7 Million	This company cultivates a wide range of pesticide-free fruits, vegetables, and leafy greens, like kale, lettuce, and basil using vertical farming. It has a large consumer base across the United States.
D3	Freight Farms	USA/ US $72 Million	The company launched Greenery S, a vertical hydroponic farm equipped with the latest equipment and five specialized systems that help cultivate various crop types round the year.
D4	AeroFarms	USA/ US $22 Million	AeroFarms is the first indoor vertical farming companies as a certified B Corporation that has developed an aeroponic technology to provide optimum conditions to plants.
D5	Grow Pod Solutions (GP)	USA/ US $15 Million	GP has developed GrowPods, automated, finely tuned, scalable, and micro-farms.
D6	Crop One Holding, Inc.	USA/ US $15 Million	The company grows food without pesticides, and in optimum conditions like temperature, light, water, humidity, and growth nutrients.
D7	Farm.One	USA/ US $7 Million	The company focuses on eliminating single-use plastic and reducing carbon footprint and water usage.
D8	FAltius Farms	USA/ US $5.9 Million	The aeroponic vertical farms built by Altius Farms are one of the largest vertical farms in the US and at the highest elevation.

Source: Emergen Research Report (2023) [8]

3.1.2 Shared Resource Efficiency Model

This study assumes that there are K vertical farms DMU_K (k = 1, ..., k). All vertical farms are engaged in the two production stages of producing intermediate goods and services and final intermediate goods and services at the same time. Where, in the first production stage, the specific factor of X_{nk} (n = 1, …, N) and the shared factor X^s_{rk} (r = 1, ..., R) of are utilized, whose production becomes the intermediate output of production inputs Z_{pk} (p = 1, ..., P) in the second stage. Since X^s_{rk} is a shared factor, we further assume that α_{rk} is the proportion allocated to be used in the first stage. In the second stage, the remaining shared factors of $(1 - \alpha_{rk})X^s_{rk}$, and the intermediate inputs Z_{pk} produced in the first stage, are used to produce the final output of Y_{mk} (m = 1, ..., M) and B_{jk} (j = 1, ..., J). Where, Y is good output (i.e., the desired output), while B is bad output (i.e., the undesired output). Under the assumption of variable returns to scale (VRS), the technical efficiency of the shared factor network DEA in these two production stages can be measured using the following Eqs. (1) and (2) models, respectively:

The efficiency model of the first production stage:

$$\max \frac{\Sigma_{p=1}^{p}\varnothing_P^1 Z_{pk^{\cdot}} + \delta^{one}}{\Sigma_{n=1}^{N} v_n X_{nk^{\cdot}} + \Sigma_{r=1}^{R} v^{sl}_{\alpha_{rk^{\cdot}}} X^s_{rk^{\cdot}}}$$

$$s.t \frac{\Sigma_{p=1}^{p}\varnothing_P^1 Z_{pk^{\cdot}} + \delta^{one}}{\Sigma_{n=1}^{N} v_n X_{nk} + \Sigma_{r=1}^{R} v^{sl}_{\alpha_{rk}} X^s_{rk}} \leq 1, k = 1,...,K$$
$$L_{rk} \leq \alpha_{rk} \leq U_{rk}, r = 1,...,R\ k = 1,...,K$$
$$v_n, v_r^{sl}, \varnothing_P^1 \geq \varepsilon, \delta^{one}\ free, m = 1,...,N;$$
$$r = 1,...,R;\ p = 1,...,P \quad (1)$$

The efficiency model of the second production stage:

$$\max \frac{\Sigma_{m=1}^{M} u_m y_{mk^{\cdot}} - \Sigma_{j=1}^{j} \rho_j B_{jk^{\cdot}} + \delta^{two}}{\Sigma_{p=1}^{p} \varnothing_p^2 z_{pk^{\cdot}} + \Sigma_{r=1}^{R} v_r^{s2}(1-\alpha_{rk^{\cdot}})X^s_{rk^{\cdot}}}$$

$$s.t = \frac{\Sigma_{m=1}^{m} u_m y_{mk} - \Sigma_{j=1}^{j} \rho_j \beta_{jk} + \delta^{two}}{\Sigma_{p=1}^{p} \varnothing_p^2 z_{pk} + \Sigma_{r=1}^{R} v^{s2}_{\alpha_r}(1-\alpha_{rk})X^s_{rk}} \leq 1, k = 1,...,K$$
$$L_{rk} \leq \alpha_{rk} \leq U_{rk}, r = 1,...,R\ k = 1,...,K$$
$$v_m, v_r^{s2}, \varnothing_P^2 \geq \varepsilon, \rho_j, \delta^{two}\ free, m = 1,...,M;$$
$$r = 1,...,R;\ p = 1,...,P \quad (2)$$

where, v_n, v^{sl}_r, ϕ^1_P represents the multipliers of the specific factors, shared factors, and intermediate goods and services in the first stage of vertical farms, respectively; v_m, v^{s2}_r, $\phi^2_P \geq \varepsilon$, ρ_j represents the multipliers of the outputs of shared factors and intermediate goods and services in the second stage. To ensure that the shared factors are not all allocated to a certain stage, the restriction formula $L_{rk} \leq \alpha_{rk} \leq U_{rk}$ is added to restrict the upper limit (U_{rk}) and lower limit (L_{rk}) of α_{rk}.

[39] suggested that if the multipliers of all shared factors and intermediate goods and services are equal, i.e., $v^{s1}_r = v^{s2}_r = v^s_r$ (r =1, ..., R), $\phi^1_P = \phi^2_P = \phi_p$ (p = 1, ..., P), then the overall production technical efficiency of the two production stages in Eq. (3) could be obtained by summing the w_1, w_2 multipliers of the Eqs. (1) and (2) models:

$$w_1 \times \frac{\Sigma_{p=1}^{p}\varnothing_P^1 Z_{pk^{\cdot}} + \delta^{one}}{\Sigma_{n=1}^{N} v_n X_{nk^{\cdot}} + \Sigma_{r=1}^{R} v^{s1}_{\alpha_{rk}} X^s_{rk^{\cdot}}} + w_2 \times$$
$$\frac{\Sigma_{m=1}^{M} u_m y_{mk^{\cdot}} - \Sigma_{j=1}^{j} \rho_j B_{jk^{\cdot}} + \delta^{two}}{\Sigma_{p=1}^{p} \varnothing_p^2 z_{pk^{\cdot}} + \Sigma_{r=1}^{R} v_r^{s2}(1-\alpha_{rk^{\cdot}})X^s_{rk^{\cdot}}} \quad (3)$$

$$\text{Making } w_1 = \frac{\Sigma_{n=1}^{N} v_n X_{nk^{\cdot}} + \Sigma_{r=1}^{R} v_r^s \alpha_{rk^{\cdot}} X^s_{rk^{\cdot}}}{\Sigma_{n=1}^{N} v_n X_{nk^{\cdot}} + \Sigma_{r=1}^{R} v^s_{\alpha_{rk^{\cdot}}} X^s_{rk^{\cdot}} + \Sigma_{p=1}^{p} \varnothing_p z_{pk^{\cdot}}}$$
$$w_2 = \frac{\Sigma_{p=1}^{p}\varnothing_P^1 Z_{pk^{\cdot}} + \Sigma_{r=1}^{R} v_r^s(1-\alpha_{rk^{\cdot}})X^s_{rk^{\cdot}}}{\Sigma_{n=1}^{N} v_n X_{nk} + \Sigma_{r=1}^{R} v^s_{\alpha_r} X^s_{rk^{\cdot}} + \Sigma_{p=1}^{p} \varnothing_p^1 z_{pk^{\cdot}}}$$

Because of the limitations of the NDEA method when dealing with shared factors, [40] established a network stochastic boundary model and used econometric methods to estimate the two-stage technical efficiency of vertical farms. The advantage of this model is that the α_{rk} value of this research model can be estimated.

Thus, the measurement of the overall production technical efficiency of the two production stages in Eq. (3) can be converted to Eq. (4):

$$\frac{\Sigma_{p=1}^{p}\varnothing_P^1 Z_{pk^{\cdot}} + \delta^{one} + \Sigma_{m=1}^{M} u_m y_{mk^{\cdot}} - \Sigma_{j=1}^{j} \rho_j B_{jk^{\cdot}} + \delta^{two}}{\Sigma_{n=1}^{N} v_n X_{nk^{\cdot}} + \Sigma_{r=1}^{R} v_r^s X^s_{rk^{\cdot}} + \Sigma_{p=1}^{p} \varnothing_p z_{pk^{\cdot}}} \quad (4)$$

According to the shared resource efficiency model proposed by [35], it can be expressed as Eq. (5):

$$\theta^* = \max \frac{\Sigma_{p=1}^{p}\varnothing_P^1 Z_{pk^{\cdot}} + \Sigma_{m=1}^{M} u_m y_{mk^{\cdot}} - \Sigma_{j=1}^{j} \rho_j B_{jk^{\cdot}} + \delta^{one} + \delta^{two}}{\Sigma_{n=1}^{N} v_n X_{nk^{\cdot}} + \Sigma_{r=1}^{R} v_r^s X^s_{rk^{\cdot}} + \Sigma_{p=1}^{p} \varnothing_p z_{pk^{\cdot}}}$$
$$s.t \frac{\Sigma_{p=1}^{p}\varnothing_P^1 Z_{pk^{\cdot}} + \delta^{one}}{\Sigma_{n=1}^{N} v_n X_{nk^{\cdot}} + \Sigma_{r=1}^{R} v_r^s X^s_{rk^{\cdot}}} \leq 1, k = 1,...,K$$
$$\frac{\Sigma_{m=1}^{M} u_m y_{mk^{\cdot}} - \Sigma_{j=1}^{j} \rho_j B_{jk^{\cdot}} + \delta^{two}}{\Sigma_{p=1}^{p} \varnothing_p z_{pk} + \Sigma_{r=1}^{R} v_r^s(1-\alpha_{rk})X^s_{rk^{\cdot}}} \leq 1, k = 1,...K \quad (5)$$
$$L_{rk} \leq \alpha_{rk} \leq U_{rk}, r = 1,...,R\ \ k = 1,..,K$$
$$v_n, u_m, v_r^s, \varnothing_P \geq \varepsilon, \rho_j, \delta^{one}, \delta^{two}\ free, n = 1,...,N;$$
$$r = 1,...,R;\ p = 1,...,P,$$
$$m = 1,...,M,\ j = 1,...,J$$

Eq. (5) is a nonlinear model. According to [39], this study adopts the linearization method to calculate the overall production efficiency θ^* after conversion, linearization and solving. First, it can be converted to Eq. (6):

$$
\begin{aligned}
&\theta^* = \max \sum\nolimits_{p=1}^{p} \eta_p z_{pk} + \sum_{m=1}^{M} u_m y_{mk^{\cdot}} - \sum_{j=1}^{j} r_j B_{jk^{\cdot}} + \delta^{one} + \delta^{two} \\
&s.t = \Sigma_{n=1}^{N} w_n X_{nk^{\cdot}} + \Sigma_{r=1}^{R} w_r^s X_{rk^{\cdot}}^s + \Sigma_{p=1}^{p} \eta_p z_{pk} = 1 \\
&\Sigma_{p=1}^{p} \eta_p z_{pk} + \delta^{one} - \left(\sum_{n=1}^{N} w_n X_{nk^{\cdot}} + \sum_{r=1}^{R} w_r^s \alpha_{rk} X_{rk^{\cdot}}^s \right) \le 0, k = 1, \ldots, K \\
&\sum_{m=1}^{M} u_m y_{mk^{\cdot}} - \\
&\sum_{j=1}^{j} \gamma_j B_{jk^{\cdot}} + \delta^{two} - \left[\sum\nolimits_{p=1}^{p} \eta_p z_{pk} + \sum_{r=1}^{R} w_r^s (1-\alpha_{rk}) X_{rk^{\cdot}}^s \right] \le 0 \\
&k = 1, \ldots, K \\
&L_{rk} \le \alpha_{rk} \le U_{rk}, r = 1, \ldots, R \;\; k = 1, \ldots, K \\
&v_n, u_m, v_r^s, \eta_P \ge \varepsilon, \rho_j, \delta^{one}, \delta^{two} \, free, n = 1, \ldots, N; \\
&r = 1, \ldots, R; p = 1, \ldots, P, \\
&m = 1, \ldots, M; j = 1, \ldots J
\end{aligned} \tag{6}
$$

In the overall efficiency solution of Eq. (6), the efficiency values of each production stage can be decomposed according to the solution results. Eq. (6) may have multiple solutions, so the individual efficiency values obtained by decomposition are not unique. Therefore, according [41], under the condition that the overall efficiency remains unchanged, the maximum production efficiency of the first stage is first obtained. Then, the market efficiency value of the second stage can be calculated. Conversely, the maximum market efficiency value of the second stage can be obtained first. Then, the production efficiency value of the first stage can be calculated based on the result. The selected order depends on the importance of the two stages of production. First, the maximum production efficiency value in the first stage can be calculated using Eq. (7):

$$
\begin{aligned}
&\max \theta_1^* = \frac{\Sigma_{p=1}^{p} \varnothing_P^1 Z_{pk^{\cdot}} + \delta^{one}}{\Sigma_{n=1}^{N} v_n X_{nk^{\cdot}} + \Sigma_{r=1}^{R} v_r^s \alpha_{rk^{\cdot}} X_{rk^{\cdot}}^s} \\
&s.t = \frac{\Sigma_{p=1}^{p} \varnothing_P^1 Z_{pk} + \delta^{one}}{\Sigma_{n=1}^{N} v_n X_{nk} + \Sigma_{r=1}^{R} v_r^s \alpha_{rk} X_{rk}^s} \le 1, k = 1, \ldots, K \\
&\frac{\Sigma_{m=1}^{M} u_m y_{mk^{\cdot}} - \Sigma_{j=1}^{j} \rho_j B_{jk^{\cdot}} + \delta^{two}}{\Sigma_{p=1}^{p} \varnothing_p z_{pk} + \Sigma_{r=1}^{R} v_r^s (1-\alpha_{rk}) X_{rk^{\cdot}}^s} \le 1, k = 1, \ldots K \\
&\theta^* = \frac{\Sigma_{p=1}^{p} \varnothing_P^1 Z_{pk^{\cdot}} + \Sigma_{m=1}^{M} u_m y_{mk^{\cdot}} - \Sigma_{j=1}^{j} \rho_j B_{jk^{\cdot}} + \delta^{one} + \delta^{two}}{\Sigma_{n=1}^{N} v_n X_{nk^{\cdot}} + \Sigma_{r=1}^{R} v_r^s X_{rk^{\cdot}}^s + \Sigma_{p=1}^{p} \varnothing_p z_{pk^{\cdot}}} \\
&w_1^* = \frac{\Sigma_{p=1}^{p} \varnothing_P^1 Z_{pk^{\cdot}} + \delta^{one}}{\Sigma_{n=1}^{N} v_n X_{nk^{\cdot}} + \Sigma_{r=1}^{R} v_{\alpha_{rk^{\cdot}}}^{sl} X_{rk^{\cdot}}^s} \le \theta^* \\
&L_{rk} \le \alpha_{rk} \le U_{rk}, r = 1, \ldots, R \;\; k = 1, \ldots, K \\
&v_n, u_m, v_r^s, \eta_P \ge \varepsilon, \rho_j, \delta^{one}, \delta^{two} \, free, n = 1, \ldots, N; \\
&r = 1, \ldots, R; p = 1, \ldots, P, \\
&m = 1, \ldots, M; j = 1, \ldots J
\end{aligned} \tag{7}
$$

where, θ^* is the optimal overall efficiency value obtained according to Eq. (6). Similarly, Eq. (7) is also a nonlinear model. The programming mode of Eq. (8) can be obtained through further linearization conversion:

$$
\begin{aligned}
&\theta_1^* = \max \sum\nolimits_{p=1}^{p} \eta_p z_{pk} + \delta^{one} \\
&s.t \; \Sigma_{n=1}^{N} w_n X_{nk^{\cdot}} + \Sigma_{r=1}^{R} w_r^s X_{rk^{\cdot}}^s = 1 \\
&\Sigma_{p=1}^{p} \eta_p z_{pk} + \delta^{one} - \left(\sum_{n=1}^{N} w_n X_{nk^{\cdot}} + \sum_{r=1}^{R} \beta_r^s X_{rk^{\cdot}}^s \right) \le 0, k = 1, \ldots, K \\
&\sum_{m=1}^{M} u_m y_{mk^{\cdot}} \\
&-\sum_{j=1}^{j} \gamma_j B_{jk^{\cdot}} + \delta^{two} - \left[\sum\nolimits_{p=1}^{p} \eta_p z_{pk} + \sum_{r=1}^{R} (w_r^s - \beta_{rk}^s) X_{rk^{\cdot}}^s \right] \le 0 \\
&k = 1, \ldots, K \\
&w_1^* = (\sum\nolimits_{p=1}^{p} \eta_p z_{pk} + \delta^{one}) \le \theta^* \\
&(1-\theta^*) \sum\nolimits_{p=1}^{p} \eta_p z_{pk} + \sum_{m=1}^{M} u_m y_{mk^{\cdot}} - \sum_{j=1}^{j} \gamma_j B_{jk^{\cdot}} + \delta^{one} + \delta^{two} \\
&-\theta^* \left(\sum_{n=1}^{N} w_n X_{nk^{\cdot}} + \sum_{r=1}^{R} w_r^s X_{rk^{\cdot}}^s \right) = 0 \\
&L_{rk} w_r^s \le \beta_{rk} \le U_{rk} w_r^s, r = 1, \ldots, R \;\; k = 1, \ldots, K \\
&w_n, u_m, w_r^s, \eta_P \ge \varepsilon, \gamma_j, \delta^{one}, \delta^{two} \, free, n = 1, \ldots, N; \\
&r = 1, \ldots, R; p = 1, \ldots, P, \\
&m = 1, \ldots, M; j = 1, \ldots J
\end{aligned} \tag{8}
$$

After obtaining the production efficiency value of the first stage, the efficiency value of the second production stage can be calculated using Eq. (9):

$$\theta_2^* = \frac{\theta^* - w_1^* \theta_1^*}{w_2^*} \tag{9}$$

Similarly, if the maximum market efficiency value in the second stage is first obtained, its linearization solution mode can be expressed as Eq. (10):

$$\theta_1^* = \frac{\theta^* - w_2^* \theta_2^*}{w_1^*} \tag{10}$$

3.1.3 Variable Setting of the Input and Output of Vertical Farms

The present study uses the dynamic network DEA model. Input items include energy generation equipment and water recycling system costs. Take power generation efficiency and water saving efficiency as the output items of the first stage. The input items of the second stage include the output of the first stage (intermediate goods and services), the number of employees, operating expenses, and the input cost of AI automation systems. The output item of the second stage is EPS, and this study uses net profit as a multi-year carry over to measure the efficiency change in each period. Details are shown in Table 2.

4 Empirical Findings and Discussion

This study used the applied statistics software DEA-Solver Professional 16.0 to set the production process of vertical farms as variable returns to scale. We used the dynamic network DEA model to analyze the operational efficiency of vertical farms. The findings can help vertical farms with low operating efficiency determine improvement strategies, determine input resources to obtain the best allocation and avoid wasting resources. The research results are as follows:

4.1 Descriptive Statistics and Analysis of The Input and Output Variables

Table 3 shows that in 2022, DMU1 invested the most in energy power generation equipment among the world's top eight vertical farms, with US 10.86 million. DMU8 invested the least, with only US 0.82 million. Regarding the cost variable of the water recycling system, DMU2 invested the most, with US 4.31 million. DMU8 invested the least, with only US 0.38 million. Regarding the intermediate output variable, DMU1 achieved the highest energy generated of US 4.68 million, while DMU7 achieved the lowest energy generated, with only US 0.56 million. Regarding profit output variable of vertical farms, DMU1 was the largest, with US 57.81 million. DMU8 was the smallest, with only US 1.52 million. This study's descriptive statistics indicate that the energy generation equipment invested in the first stage, the higher the inter-mediate output of the first stage of vertical farms. However, increasing intermediate output in the first stage may not necessarily improve market efficiency in the second stage. It may be caused by the high electricity cost in the second stage. Therefore, the operational efficiency of vertical farms is worth further analysis.

Table 2. Description of the input and output variables of vertical farms

	Variable	Variable definition description	Unit
Environmental protection and green energy input item	Energy generation equipment	Solar or wind power costs	Million
	Water recycling system costs	Environmental protection material input and lighting cost	Million
Intermediate output	Energy generation benefits	The value of solar or wind power	Million
	Benefits of water recycling	Amount of water saved annually	Liter
The second stage input item	Number of employees	Number of employees	People
	Operating expenses	Including water and electricity charges	Million
	AI automatic monitoring cost	Automated irrigation and plant growth monitoring system	Million
Interdepartmental link	Operating income	Net revenue after deducting sales returns and discounts	Million
Final output	EPS	Net profit after tax ÷ number of common shares outstanding	US
Inter-period carry over	Profit	presented in the financial statements net profit after tax	Million

Table 3. Descriptive statistics of the input and output variables of vertical farms

Variable		Average	Maximum value	Minimum value	Standard deviation
Environmental protection and green energy input item	Energy generation equipment	US 3.26 Million	US 10.86 Million	US 0.82 Million	US 0.26 Million
	Cost of the water recycling system	US 1.28 Million	US 4.31 Million	US 0.38 Million	US 0.08 Million
Intermediate output	Energy generation benefits	US 1.65 Million	US 4.68 Million	US 0.56 Million	US 0.05 Million
	Benefits of water recycling	468.5Million Liter	1238.5 Million Liter	135.65 Million Liter	28.65 Million
The second stage input item	Number of employees	115 People	312 People	36 People	5.68
	Operating expenses	US 8.68 Million	US 12.36 Million	US 0.88 Million	US 0.35 Million
	AI automatic monitoring cost	US 4.68 Million	US 6.67 Million	US 0.58 Million	US 0.35 Million
Interdepartmental Link	Operating income	US 38.58 Million	US 103 Million	US 5.9 Million	US 0.67 Million
Final output	EPS	US 0.58	US 0.97	US 0.13	US 0.015
Inter-period carry over	Profit	US 13.58 Million	US 57.81 Million	US 1.52 Million	US 0.78 Million

4.2 Analysis of The Total Operating Efficiency of Vertical Farms Each Year

The present study used the dynamic network DEA Model to measure the operating efficiency of vertical farms. To avoid the possibility of multiple solutions in the mathematical model, we assumed that the overall efficiency remained unchanged. Then, the maximum production efficiency in the first stage was obtained and the market efficiency value in the second stage was measured. Conversely, the maximum market efficiency value of the second stage could be obtained first. Then, the production efficiency value of the first stage could be measured. [41] suggested that operators could make decisions based on the operating efficiency value of each stage to improve operational efficiency and avoid resource waste.

Table 4 shows that the average total operating efficiency of D2 and D3 was the highest, which was 1. This indicates that the input and output resources of these two vertical farms were optimally allocated, making them good models for all vertical farms. In contrast, the average total operating efficiency value of D6 was the smallest at 0.752. This indicates that there is still 24.8% room for improvement. D1 had the largest operating scale and the largest annual revenue. However, D1's average total operating efficiency was only 0.882, ranking 5th, indicating there is 11.8% room for improvement. Therefore, D1 still has room for improvement in allocating its inputs and outputs. D8 had the smallest operating scale and the smallest annual revenue; its average total operating efficiency was 0.902. Based on the above, there was no correlation between the revenue of vertical farms and their total operational efficiency.

4.3 Impact of COVID-19 on the Operating Efficiency of Vertical Farms

The AI market efficiency of the second stage in this study was the interdepartmental link from the energy generation benefits generated in the first stage to the market efficiency of the second stage. The output item of this stage was the earnings per share (EPS), and the profit was regarded as the multi-year carry over. Table 4 shows the empirical results of the overall operating efficiency of vertical farms, and their production and market efficiencies in two production stages. Table 4 shows that the overall total operating efficiency of vertical farms between 2018 and 2022 was 0.886. This means that vertical farms have 11.4% room for improvement in overall efficiency. Furthermore, the production efficiency of the first stage was 0.815, and the market efficiency of the second stage was 0.938. These findings indicate that the AI market efficiency of vertical farms in the second stage was better. This result is consistent with [42]. In other words, the operational efficiency of the second stage is higher than the energy generation efficiency of the first stage. In addition, after obtaining the intermediate output of the first stage, the vertical farm can better allocate resources in the second stage and create operating profits and operating efficiency. This means that the energy generation efficiency of the first stage of the vertical farm may be low, which indirectly results in high operating costs in the second stage, and finally reduces the overall operating efficiency of the vertical farm.

To analyze the impact of COVID-19 on the operating efficiency of vertical farms, the sample period was divided into three periods in Table 5, namely, the pre-pandemic period (2018-2019), the pandemic period (2020-2021) and the post-pandemic period (2022); the operating efficiency of each period was compared. Table 5 shows that in terms of overall efficiency, there was little difference between the operating efficiency of the first stage and the AI market operating efficiency of the second stage in the operating efficiency during the same period; the AI market efficiency of the second stage remained at the highest level. Through exploring the operating efficiency values of the same efficiency in the three different periods of the COVID-19 pandemic, according to the results of the Kruskal-Wallis test, a non-parametric method for testing, there was no significant difference in the overall efficiency and the market efficiency of the second stage in the three periods at the significant level $\alpha = 0.05$, and the H value was lower than 5.99. However, the efficiency of the first stage during the pandemic period (2020-2021) was significantly better than that of the pre-pandemic period (2018-2019) and the post-pandemic period (2022). Moreover, under the condition that the significant level $\alpha = 0.05$, the H value was greater than 5.99. This indicates that the COVID-19 pandemic significantly impacted the efficiency of the first stage of vertical farms. These findings suggest that, in addition to its impact on people's health, COVID-19 is prompting vertical farm operators to pay more attention to energy generation functions. This can further improve the efficiency of energy generation in the first stage of the vertical farm.

Table 4. Total operating efficiency values of vertical farms from 2018 to 2022

DMU	2018	2019	2020	2021	2022	Average efficiency	Ranking
D1	0.871	0.862	0.903	0.870	0.911	0.882	5
D2	1.000	1.000	1.000	1.000	1.000	1.000	1
D3	1.000	1.000	1.000	1.000	1.000	1.000	1
D4	0.936	0.866	1.000	0.841	0.917	0.887	4
D5	0.831	0.862	0.817	0.901	8.02	0.831	6
D6	0.726	0.786	0.713	0.738	0.816	0.752	8
D7	0.811	0.795	0.826	0.781	0.806	0.805	7
D8	0.936	0.885	0.921	0.858	0.891	0.902	3
Average value	0.853	0.822	0.916	0.803	0.873	0.863	NA
Maximum value	1.000	1.000	1.000	1.000	1.000	1.000	NA
Minimum value	0.726	0.786	0.713	0.738	0.802	0.752	NA
Standard deviation	0.16	0.21	0.08	0.13	0.17	0.22	NA

Table 5. Operating efficiency values and the K-W tests of vertical farms

Period	Overall efficiency				Production efficiency of the first stage				Production efficiency of the second stage			
	Average mean	Standard deviation	Max	Min	Average mean	Standard deviation	Max	Min	Average mean	Standard deviation	Max	Min
2018~2022	0.886	0.121	1.000	0.526	0.835	0.105	1.000	0.386	0.938	0.142	1.000	0.688
2018~2019 (the pre-pandemic period)	0.904	0.113	1.000	0.586	0.802	0.127	1.000	0.416	0.973	0.113	1.000	0.726
2020~2021 (the pandemic period)	0.856	0.151	1.000	0.423	0.902	0.132	1.000	0.332	0.857	0.138	1.000	0.598
2022 (the post-pandemic period)	0.898	0.125	1.000	0.535	0.818	0.156	1.000	0.410	0.984	0.127	1.000	0.705
H value of the Kruskal-Wallis test	2.23				6.12*				1.56			

* Indicates significance under the condition that $\alpha < 0.05$

Table 6 shows the operating efficiency of eight vertical farms in the two phases from 2018 to 2022. Energy generation benefits are regarded as output items, and period links are regarded as profits. The first stage energy production efficiency value is 0.835. The most efficient one in the first stage is D3, with an efficiency value of 1. D1 The first stage has the lowest production efficiency. This shows that the D1 vertical farm cannot achieve the optimal allocation of resources in the energy generation stage.

Table 6 shows that the D3 vertical farm has the highest AI market efficiency of the second stage, and its efficiency value is 1. This finding indicates that D3 had the best AI market efficiency of the second stage with an interdepartmental link to the production efficiency of the first stage. It can optimally allocate all input factors of its environmental protection and green energy inputs and shared resource inputs. Although the D4 vertical farm has the lowest AI market efficiency of the second stage, it also reached 0.902. Therefore, the biggest problem in vertical farm operations is still the production efficiency of the input and output of the first stage of energy equipment. The results of this study also highlight the poor allocation of practical production resources in the first stage of vertical farms, leading to problems of power generation, energy shortages, and high equipment costs, and also affecting the operational efficiency of the second stage of vertical farms.

Table 6. Average values of the total operating efficiency, production efficiency in the first stage, and production efficiency in the second stage of each vertical farm

DMU	Average values of the total operating efficiency	Average values of the production efficiency in the first stage	Average values of the production efficiency in the second stage
D1	0.882	0.755	0.903
D2	0.906	0.825	0.963
D3	1.000	1.000	1.000
D4	0.887	0.781	0.902
D5	0.831	0.851	0.915
D6	0.752	0.826	0.936
D7	0.805	0.792	0.905
D8	0.902	0.843	0.971
Average value	0.863	0.835	0.938
Maximum value	1.000	1.000	1.000
Minimum value	0.752	0.755	0.903
Standard deviation	0.18	0.23	0.18

4.4 Analysis of The Relative Efficiency And Slack Variable of Vertical Farms

The above research results indicate that the operating efficiency of the vertical farms analyzed in this study is relatively low. This suggests that there are issues of poor resource allocation and resource waste in vertical farms. Therefore, this study established a linear programming model for efficiency evaluation using the dynamic network DEA method and the technical efficiency of the eight vertical farms was compared. Based on the output, the CCR and BCC models were adopted, respectively, to measure the relative operating efficiency of vertical farms. Then, this study estimated the slack variable adjustment ratio of the input and output of the BCC model. The findings can help vertical farms improve resource allocation and solve the problem of waste in resource costs.

Table 7 shows that D3 is the vertical farm with the best total operating efficiency, and all resources reached optimal allocation. D6 is the vertical farm with the worst total operating efficiency. Among D6's input items, water-saving equipment should be reduced by 6.72%, the number of employees should be reduced by 25.26%, and the operating expenses should be reduced by 76.53%. As such, the operating income of the interdepartmental link may increase by 81.53%; the profit of inter-period carry over may increase by 88.72% so that the operational efficiency would be improved. Similarly, if D7 can reduce its investment in energy power generation equipment, water-saving equipment, AI automatic monitoring costs and operating expenses by 18.46%, 2.62%, 9.25% and 42.54% respectively, then its operating income may increase by 26.81% and its profit growth 51.32%. Table 7 shows that among all the input factors of vertical farms, the operating expense is the most unbalanced, which should be reduced by 38.68% on average. Table 7 also illustrates the intractable issue of the high operating expenses (power and water costs) of vertical farms worldwide. Furthermore, in future operating strategies, if vertical farms can optimize the allocation and combination of all input and output factors, they may improve their operational efficiencies and increase their profits.

Table 7. Input items, interdepartmental links, and inter-period carry over slack variable adjustment ratio of vertical farms in 2022

DMU	Input items (%)					Interdepartmental link (%)	Inter-period carry over (%)
	Energy generation equipment	Inputs in water-saving equipment	AI automatic monitoring cost	Number of employees	Operating expense	Operating income	Profit
D1	0.000	0.000	-16.8	-21.32	-35.61	28.65	37.25
D2	-8.5	0.000	0.000	-18.35	-28.71	23.7	28.95
D3	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D4	-12.52	-3.67	-6.71	-12.31	-28.92	38.25	48.26
D5	-6.89	0.000	-12.30	-15.28	-7.43	30.84	52.38
D6	0.000	-6.72	0.000	-25.26	-76.53	81.53	78.72
D7	-18.46	-2.62	-9.25	0.000	-42.54	26.81	31.32
D8	-22.73	0.000	0.000	0.000	-26.77	20.35	36.81
Average value	-7.65	-2.06	-4.28	-8.73	-38.68	31.92	35.65

Note. 1. The fields of "Energy generation equipment," "inputs in water-saving equipment," "AI automatic monitoring cost," "number of employees" and "operating expenses" represent the adjustment range required to achieve relative efficiency; Adjustment range = (projected value - original value) ÷ original value ×100%. 2. The field values of the interdepartmental link "operating income" and the inter-period carry-over "profit" represent the adjustment ratio required to achieve relative efficiency; adjustment ratio = (projected value - original value) ÷ original value ×100%.

5 Discussion and Implications

The research results show that in the two-stage operation efficiency, the energy generation efficiency in the first stage is low, which will lead to higher operating costs (electricity and water bills) in the second stage, affecting the overall operation efficiency. Therefore, in the future operation strategy of vertical farms, the optimal input-output combination of energy generation must be considered to avoid resource waste. The research also suggests that vertical farm operators may move toward optimizing agriculture. For example, the upper layer of vegetables grown in vertical farms may block the sunlight of the lower layer of vegetables. Thus, LED lights are required to accelerate photosynthesis through artificial light. However, using artificial lights all day may increase operating expenses. Additionally, different crops respond differently to various combinations of light. Therefore, it is recommended that vertical farm operators should refer to expert advice for spectral factors, light angle, Photosynthetic Photon Flux Densit (PPFD), and other factors to set the correct lighting angle of various crops, with appropriate LED lighting to avoid resource waste. On the other hand, in addition to LED lighting, vertical farm operators can also try to let crops receive natural lighting. For example, A-shaped vegetable towers can be built, which rotate slowly to ensure that all crops receive equal sunlight. These measures may allow vertical farms to use low input costs to elicit high output.

Additionally, this study's slack variable analysis results show that the poor operating efficiency of vertical farms was primarily due to a lack of optimal allocation and combination of input and output factors, resulting in excessive operating costs and waste of resources. On the other hand, this study also shows that the operating expenses of all vertical farms must be adjusted to optimal levels. Therefore, it is suggested that during the operation of vertical farms in the future, necessary attention should be paid to the cost of electricity, machine maintenance, rent, advertising, and marketing. Further, more energy-saving equipment should be adopted, farming technology and planting density should be optimized, and digital marketing should be used to reduce operating expenses. For example, regarding specific marketing practices, vertical farm operators can showcase the freshness of their agricultural products to the public through functions such as creating, sharing, and exchanging ideas, opinions, and experiences available on social media. They can also demonstrate the fact that their agricultural products are locally cultivated and sustainably produced. They can even provide vertical farms a story with a price to not only further enable the public to focus on food safety issues but also attract the attention of more potential consumers. Regarding technology, it is suggested that vertical farm operators can improve the quality and quantity of agricultural products with the assistance of artificial intelligence software. For example, smart agricultural integration systems can be used to control the growth process of crops. The environmental monitoring sensor and monitoring system set up in the front site can be applied to collect humidity, sunshine, soil moisture, and other information, or robot technology can be utilized to cut down labor costs. These strategies may help reduce operating expenses.

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