Bio-economic modelling of high-tech greenhouse production systems in China

Xinyuan Min

Propositions

1. Price and policy uncertainty influence the economic feasibility and the timing of greenhouse investment in China.
   (this thesis)
2. Stakeholders' preferences affect the optimal greenhouse design.
   (this thesis)
3. The inherent ambiguity in human language leads to conceptual imprecision.
4. Curiosity is the most important quality for conducting interdisciplinary research.
5. Policy recommendations in research articles are only local optimisations of complex real-world problems.
6. Period products should be readily available in every workplace.

Propositions belonging to the thesis, entitled

Bio-economic modelling of high-tech greenhouse production systems in China

Xinyuan Min
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Bio-economic modelling of high-tech greenhouse production systems in China

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Xinyuan Min

Thesis

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This too shall pass

Contents

Chapter 1 General Introduction

1.1 Background

China's agriculture is shifting towards more efficient and sustainable production systems. This transition is driven by several factors: changing dietary patterns that favour more meat and vegetables (Huang, 2016), increasing consumer willingness to pay for high-quality agricultural products (Sheng & Song, 2019), a shortage of young farmers (Liu et al., 2023), diminishing quality of arable and (Larson, 2013), and escalating soil contamination (Liu et al., 2013). Greenhouse horticulture can offer a solution to these challenges.

The terms "greenhouse horticulture", "protected horticulture", and "controlled environment agriculture" are often used interchangeably. They all denote a core concept: modifying the environment to provide crops with favourable growth conditions (Marcelis et al., 2019). For the remainder of this introduction, the term "greenhouse horticulture" will be used. These systems are highly land-use efficient and are often located near urban areas, enabling high-yield and quality crop production with extended growing seasons.

Greenhouse horticulture encompasses a wide array of designs with varying technological levels. In China, the prevalent types are single-span plastic tunnels or solar greenhouses, covering 2.7 million hectares (ha). These conventional low-tech production systems offer limited climate control, with heating often unapplied. In contrast, multi-span plastic greenhouses span 0.99 million ha, and high-tech glasshouses only account for 9000 ha (Sun et al., 2019). In line with the trend towards agricultural modernization, this thesis will focus on key factors in the economic feasibility of high-tech greenhouses with relatively comprehensive climate control capabilities, namely multi-span plastic greenhouses and glasshouses.

The government's agriculture policy has shifted towards promoting more industrialized and capital-intensive forms of agricultural production (Huang & Gao, 2013; Rogers et al., 2021). Over the past decade, there have been continuous efforts from the Chinese government to support large-scale modern farms. Governmental support takes many forms, both financial and non-financial. Financial support includes subsidies for qualified agriculture projects and government-directed loans with favourable interest rates (Gale, 2013; Huang, 2017). Non-financial support includes access to land, the establishment of horticultural demonstration centres, and extension services (Cai et al., 2022; J. Huang & Rozelle, 2014).

The producers in modern agriculture production in China are predominantly agribusiness firms, including firms that were not traditionally associated with agriculture, such as real estate developers or IT companies (Huang, 2017; Wang et al., 2023). These agribusiness firms differ significantly from traditional producers, such as rural households, in that they operate on a large scale and have substantial capital resources. Their rise has been greatly facilitated by local governments, which aim to delegate these firms as agents to compete for and implement centrally-funded agricultural projects (Gong & Zhang, 2017).

Many modern agricultural programs are operated in a project-based manner. The investment capital for these projects is typically raised through matching funds from three entities: the central government, local governments, and agribusiness firms (Gong & Zhang, 2016). For example, in Beijing, the district-level government provides grants that cover 30% of the greenhouse construction costs, and the municipal government offers up to an additional 20% funding for eligible greenhouse projects (Beijing Municipal Bureau of Agriculture and Rural Affairs, 2022). The remaining funds are contributed by the agribusiness firm.

The substantial financial backing from the government sparked a surge in greenhouse investment in China. In 2017 alone, the construction area of large-scale glasshouses (above 5 ha) surpassed 400 ha, with a total investment capital of eight billion RMB (MOA, 2018). From 2020 to 2022, the area of newly constructed multi-span greenhouses exceeded 1288 ha (Wang et al., 2023). Modern multi-span greenhouses can be found in various places across China, including provinces such as Shandong, Gansu, Hebei, and Anhui, as well as major cities like Beijing and Shanghai. Zhong et al. (2020) refer to the expansion of greenhouses in China as "state-led food localization".

1.2 Problem statement

1.2.1 Adaptive greenhouse designs for different regions in China

Despite the rapid development, there is an ongoing debate about the economic feasibility of these high-tech greenhouses in China. This concern is well-founded, as many greenhouse firms are finding it challenging to make a profit (Wang et al., 2023). Intriguingly, a negative correlation seems to exist between the technological level of a greenhouse and its profitability; the most technologically advanced greenhouses tend to yield the lowest economic returns (MOA, 2018). One explanation for this could be that the designs of these greenhouses have often been directly imported from countries such as the Netherlands, without sufficient adaptation to the local climatic and market conditions in China. Given China's diverse climatic and market conditions, the appropriate designs are likely to vary across different regions.

The degree of climate control within a greenhouse is determined by the presence and capacity of various design elements, such as heating, cooling, lighting, and CO_2 dosing systems. While a more technically advanced greenhouse has better climate control capabilities, it generally incurs higher investment and operating costs. The design of greenhouse production systems represents a multi-factorial optimization problem, involving the selection of the best combination of design elements to achieve desired outcomes (Van Henten et al., 2006). However, existing studies on greenhouse design optimization in China largely focus on one or two factors at a time (e.g., Luo et al., 2005a; Wang et al., 2014). There is limited knowledge regarding the most suitable combinations of greenhouse design elements for different regions in China.

When it comes to selecting the optimal greenhouse design, one should not only consider the economic performance but also the environmental aspect. While high-tech greenhouses are highly efficient in terms of water and chemical use, there is growing concern about the high CO_2 emissions of greenhouse production (Zhou et al., 2021). Previous studies often focus on either economic performance (Vanthoor et al., 2012) or environmental impact (Antón et al., 2012; Naseer et al., 2022a; Zhou et al., 2021). Although some studies (e.g., Naseer et al., 2021; Torrellas et al., 2012) examined both the economic and environmental performance of various greenhouse designs, they assessed these dimensions separately. Such a narrow focus in previous studies fails to account for the varying priorities of investors and policy makers regarding the economic and environmental performance of greenhouse investment. There is a need for an integrated approach that assesses greenhouse designs considering stakeholder priorities in both economic and environmental dimensions.

1.2.2 Greenhouse investment under uncertainty

The economic feasibility of greenhouse investments is subject to multiple sources of uncertainty, including price and policy uncertainty. Most agricultural commodity markets are characterized by a high degree of price volatility (IMF & UNCTAD, 2011). The dependence of high-tech greenhouse production on energy, a commodity known for its high price volatility (Pindyck, 1999), makes its economic return even more volatile. A limitation of previous studies on greenhouse economic assessment is the use of deterministic prices (e.g., Shaw et al., 2004; Vadiee & Martin, 2013; Vanthoor et al., 2012). Accounting for uncertainty in input and output prices can enhance the robustness of greenhouse economic assessments.

Policy uncertainty adds an additional layer of complexity to greenhouse investments. As previously stated, government support has driven the rapid development of China's high-tech greenhouse sector over the past decade. This naturally leads to the question of how Chinese investors might respond to more uncertain future subsidy policies. In 2023, China released its first national development plan for the protected horticulture sector, setting a target to construct a number of high-tech greenhouses in major urban cities by 2030. Considering that government subsidy programs usually have a limited duration, it is reasonable to anticipate that the current subsidy scheme may be phased out at some point after these stated goals are achieved. Previous studies have shown that investors make investment decisions strategically in anticipation of policy uncertainty (Linnerud et al., 2014; Nagy et al., 2023; Yanore et al., 2023). Traditional investment appraisal methods, however, fall short of adequately addressing the influence of policy uncertainty on irreversible investment decisions. As such, a valuation method that incorporates the value of investment flexibility under policy uncertainty is necessary.

1.2.3 Stakeholder preferences for emerging technologies

The transition towards increased digitalisation and automation is an inevitable trend in the greenhouse sector (King, 2017; Verdouw et al., 2021). Significant advancements have been made in sensor and automation technologies for greenhouse operations (van Henten, 2019). These technologies are expected to be gradually adopted and diffused in the near future. While studies on sensor and automation technologies in agriculture are largely limited to arable or livestock farming (e.g., Hafezalkotob et al., 2018; Miller et al., 2019; Rutten et al., 2018; Van De Gucht et al., 2018), to our knowledge, there is no comprehensive assessment of such technologies in the greenhouse sector.

Understanding the preferences of key stakeholders, such as growers, investors, policy makers, and technology suppliers, is essential to facilitate the further adoption and diffusion of these technologies. However, a separation between invention and adoption is often observed in existing agricultural innovation studies (de Oca Munguia & Llewellyn, 2020). Technology assessment studies typically focus on the functionality of technology, while the preferences of the users of the technology remain largely invisible (McCampbell et al., 2023). In contrast, innovation adoption literature tends to focus on the characteristics of the adopter and the general farming context, with less attention paid to the attributes of the technology itself (Shang et al., 2021). An evaluation of sensor and automation technologies for greenhouse operations from a multi-stakeholder perspective is lacking in the literature.

1.3 Research objectives

The overall objective of this dissertation was to assess the economic feasibility of greenhouse investments and to identify greenhouse designs, as well as sensor and robotic technologies, that align with the preferences of multiple stakeholders in China. To achieve the overall objective, the following four sub-objectives were derived:

1. To develop a bio-economic model that assesses the economic feasibility of greenhouse investments, taking into account input and output price uncertainty.
2. To develop an optimization framework that identifies greenhouse designs that are optimally adapted to regional climatic and market conditions, considering the varying priorities of investors and policy makers for economic and environmental performance.
3. To examine the impact of uncertainty in output price and the abolition of subsidy policies on the timing of investment in high-tech greenhouses.
4. To analyse the preferences of different stakeholder groups in the Chinese greenhouse sector for sensor and robotic technologies.

1.4 **Outline**

The dissertation is divided into six chapters, i.e., a general introduction (Chapter 1), four research chapters (2-5) that elaborate on the beforementioned sub-objectives, and the general discussion (Chapter 6). Figure 1 shows a schematic outline of the dissertation.

Chapter 2 addresses the first research objective by developing a bio-economic model that assesses the economic feasibility of a greenhouse investment for tomato production. Taking into account fluctuations in tomato and natural gas prices, a Monte-Carlo simulation approach was used to obtain the probability distributions of the Net Present Values (NPVs) of a representative Venlo-type glasshouse for cherry tomato production in four locations: Jinshan (East China), Langfang (North China), Weifang (East China), and Pingliang (Northwest China), with different climatic and market conditions. The bio-economic model developed in this chapter was used for further analysis in Chapters 3 and 4.

Chapter 3 addresses the second research objective by developing an optimization framework that identifies optimal greenhouse designs in terms of both economic and environmental performance for the four locations. The bio-economic model developed in Chapter 2 was used to simulate the yield, energy use, and economic performance of different greenhouse designs. A genetic algorithm was used to explore the large solution space in order to reduce the computational effort. The overall performance of the greenhouse design was evaluated using a directional distance function, which incorporates stakeholder priorities for economic and environmental performance through the directional vector. The overall performance was evaluated under three price scenarios to identify greenhouse designs that are robust to price uncertainty.

Chapter 4 addresses the third research objective by investigating how the uncertainty about the abolition of subsidy scheme influences the optimal investment timing of greenhouse investment in China. The study employed real options analysis and modelled the evolution of the current subsidy scheme as a Poisson jump process. This process is governed by the subsidy level and a subsidy termination risk factor. The least squares Monte Carlo method was used to approximate the optimal investment timing and value of waiting under various combinations of subsidy level, subsidy termination risk factor, and tomato price evolution process.

Chapter 5 addresses the fourth research objective by developing a performance score for sensor and robotic technologies that combines stakeholder preferences and attribute scores.

Four stakeholder groups, i.e., growers, investors, technology suppliers, and policy makers, were identified. To bridge the gap between technology assessment and innovation adoption, the evaluation framework used the technology attributes defined in the Diffusion of Innovation theory. The Bayesian best-worst method was used to elicit stakeholder preferences and expert-rated technology scores for each attribute. Combining stakeholder preferences with expert-rated technology scores produced a probabilistic performance score for each technology.

Chapter 6 provides a general discussion of the thesis. This chapter discusses the approaches and findings across the research chapters and elaborates on the implications of the findings for business stakeholders and policy makers. It also outlines the limitations of the study and offers recommendations for future research. The chapter ends with the main conclusions of the dissertation and ideas for future research.

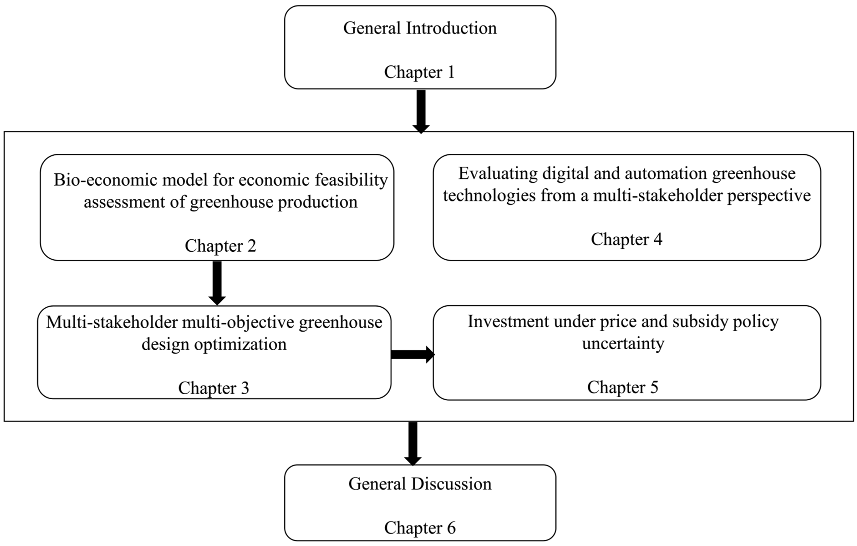

Figure 1.1. Schematic outline of the dissertation.

Chapter 2 Economic Feasibility of Glasshouse Tomato Production in China — a Bio-economic Stochastic Modelling Approach

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Abstract

Glasshouse investments are booming in China, even though little is known about the economic feasibility and uncertainty of such investments. This study employed a bio-economic model to assess the economic feasibility and uncertainty of an investment in a Venlo-type glasshouse for cherry tomato production in four regions in China: Jinshan, Langfang, Weifang, and Pingliang, with different climate and market conditions. A bio-physical model for tomato yield and energy use simulation was calibrated with the climate and production data from 2019 to 2020 of a commercial glasshouse in Shanghai, China. The average yield and energy use for each region were simulated with the temperature set points provided by a grower and 30-year climate data. The distributions of the Net Present Values (NPVs) were determined using Monte Carlo simulation which addressed uncertainty due to stochastic tomato and natural gas prices. The economic outcome of tomato glasshouse investment varies across regions, with a mean NPV ranging from −957.8 ¥ m^{-2} for Weifang, to 477.0 ¥ m^{-2} for Pingliang. A sensitivity analysis suggests that variations in natural gas prices have larger impacts on the net cash flow than tomato prices. This study contributes to the research on glasshouse modelling by introducing seasonality and uncertainty of prices in a bio-economic model of a glasshouse farm. The results of this study can inform investors of the economic outcomes and the risks of glasshouse investments. They can also aid Chinese local governments to design agricultural support policies that suit the regional climate and market conditions.

Keywords

Bio-economic modelling, glasshouse, regional climate, energy, investment uncertainty

2.1 Introduction

China is shifting from traditional labour-intensive agriculture to modern capital-intensive agriculture. Since 2013, modernizing agriculture has been a top priority for the Chinese government (Ye, 2015). One manifestation of agriculture modernization is the development of protected horticulture or greenhouses. Growing crops in a controlled and protected environment reduces the weather dependency of crop production and greatly boosts crop yield (Van Straten & Van Henten, 2010).

By 2018, the total area of protected horticulture in China reached 1.89 million ha, 66.6% covered by plastic tunnel greenhouses, 30.5% covered by solar greenhouses. Both types of greenhouses have little or no climate control ability. The area of modern multi-span greenhouses (plastic or glass) was 54,338 ha, only 2.9% of the total protected horticulture area. Only 9000 ha of multi-span greenhouses were covered with glass, accounting for less than 0.25% of the total area of protected horticulture in China (Sun et al., 2019). Most of the glasshouses in China are small in size and mainly used for research or demonstration purposes. Large-scale commercial production with a glasshouse is not common, as enterprises are still struggling to make a profit (K. Yang, personal communication, December 5, 2019).

In recent years, the greenhouse sector in China has seen an influx of investment capital (Hairong & Yiyuan, 2015; Siekman, 2018). From 2016 to 2018, more than 400 ha of glasshouses were built, with a total investment capital of eight billion RMB (Ministry of Agriculture of the People's Republic of China, 2018). A number of high-tech glasshouses have been built with the aid of local governments as demonstrations to promote the modern way of agricultural production in China (Jiang & Yu, 2008). The capital for the initial investments of these investments were usually contributed by public (local governments or state-owned enterprises) and private partners, the latter are often responsible for the day-to-day operation and maintenance (Rankin et al., 2016). The driving force of the increasing investment might be the huge market potential of high-end agricultural products in China. Faced with Chinese consumers' increasing demand for quality agricultural products, shortage of professional farmers, mounting labour costs, and declining availability of arable land, the limitations of traditional tunnel or solar greenhouses are more and more obvious (Zhou & Feng, 2002). Instead, investments in modern glasshouses are expected to be profitable in the future (Zhou & Feng, 2002).

Despite the increasing investment in glasshouses, only a few economic feasibility studies have been conducted for China. The existing glasshouse economic evaluation studies in China (Wang et al., 2017; Xue, 2017) used relatively simple economic models: they adopted production data of a short timespan from a specific location and used weather data from a particular year, which makes it difficult to generalize results to other regions with different climate conditions. China is a country with very diverse climatic and market conditions. Climate conditions determine the duration of the production cycle. Market conditions determine the costs and the revenue that can be generated from production. To conduct economic feasibility studies that are generalizable, the economic models should be able to accommodate local climate and regional market price data as inputs and generate tailored estimates as model outputs.

Modelling glasshouse production essentially involves a complex interplay of multiple biophysical processes between the outdoor climate, energy input, indoor climate, and the realized yield (Van Straten & Van Henten, 2010). Simply pursuing a high yield could require an economically sub-optimal energy use. Vice versa, minimizing the energy input regardless of yield would not make optimum use of the superiority of modern glasshouses. Systematic modelling should include the interdependent relationships between climate, energy, the yield of the glasshouse system (Dai & Luo, 2006; Van Der Ploeg & Heuvelink, 2005). In this regard, a glasshouse should not be viewed as a stand-alone biophysical system with static material input and output flows, but a dynamic system that interacts with the external market environment.

Just as with many food systems, the challenges associated with the glasshouse system cut across many disciplinary domains and should be addressed in a multidisciplinary or even interdisciplinary manner (Fresco et al., 2021). The integration of biophysical and economic models is necessary for the systematic economic evaluation of glasshouses. Examples of such studies can be found in Jones et al. (1990), Vanthoor et al. (2012), and Naseer et al. (2021). One shortcoming of these studies lies in the use of deterministic prices in the assessment of the economic feasibility. Prices of inputs and outputs are stochastic by nature, in particular those of agricultural products and energy. The result calculated using deterministic prices is only a ‘snapshot’ of one of the economic outcomes out of many possible market conditions. Including stochastic prices in the evaluation can provide a more complete understanding of the economic prospect of glasshouse investment (Gebrezgabher et al., 2012; Platon & Constantinescu, 2014).

This study aims to analyse the economic feasibility of investing in a 1.4-hectare Venlo-type glasshouse for cherry tomato production in four regions in China with different climate characteristics: Jinshan (Shanghai, East China), Langfang (Hebei, North China), Weifang (Shandong, East China), and Pingliang (Gansu, Northwest China). By combining a biophysical simulation model with an economic model, this study analyses the economic feasibility of a glasshouse investment under different climate and market conditions. By further exploring the economic outcomes under different temperature management strategies, this study reveals the dependencies between outdoor climate, temperature management strategies, energy use, indoor climate, yield, and ultimately, the profitability of the glasshouse. This study contributes to the literature on bio-economic modelling of glasshouse by introducing uncertainty in input and output prices in an integrated biophysical-economic model of a glasshouse farm. The results of this study can inform agricultural investors in China of the economic outcomes and the risks of glasshouse investments and can aid growers to formulate temperature management strategies. They can also aid Chinese local governments to design agricultural support policies that suit the regional climate and market conditions.

The remainder of this paper proceeds as follows: Sections 2.2 describes the methods and modelling framework. This is followed by the presentation of the data on glasshouse configuration, yield, and energy use simulation, and especially the sampling strategies of stochastic prices, in section 2.3. Section 2.4 presents the results of the model, the sensitivity analysis, and the break-even tomato and heating energy prices in the four regions. The paper ends with Discussion and Conclusions.

2.2 Methods and modelling framework

Figure 2.1 presents a schematic description of the modelling framework used in this paper. The modelling framework consists of two parts: the biophysical model of tomato yield and energy consumption, and the economic model (combined with Monte Carlo simulation) in which seasonal stochastic prices of tomato and heating energy were plugged in for the cash inflow and outflow simulation. A clear definition of the glasshouse configuration in terms of construction and installation details is needed for the biophysical model and the estimation of the initial investment costs.

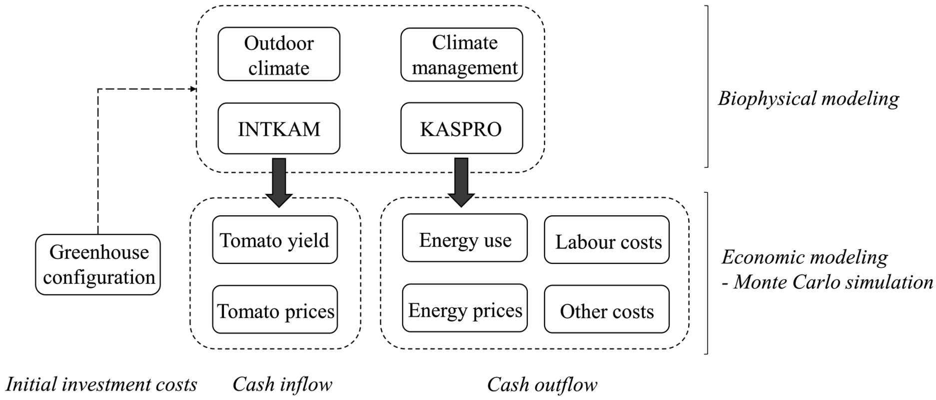

Figure 2.1 Schematic description of the modelling framework.

The broadly validated crop model INTKAM (Marcelis et al., 2009) and the greenhouse climate model KASPRO (De Zwart, 1996) were employed to simulate tomato yield and energy use for each region. The model inputs for the INTKAM-KASPRO model are hourly outdoor climate characteristics (solar radiation, temperature, sky temperature, humidity, wind speed), glasshouse configuration and climate management strategy (heating, ventilation, screen closure), and crop management strategies (e.g., stem density, fruit pruning, topping date). Production data from 2019 to 2020 of a glasshouse in Jinshan, Shanghai, were used for model calibration (there was no calibration for the other three regions due to the lack of production data). The calibration results (see Appendix 2A) showed that the INTKAM-KASPRO model can give realistic predictions for Shanghai climate, which lends credibility to the generalizability of INKKAM-KASPRO model in the other three regions.

The model outputs of the economic model are the distributions of annual net cash flow and the Net Present Value (NPV) of the tomato glasshouse investment. NPV is a widely used criterion to evaluate investment opportunities. The NPV takes the time value of money into consideration by discounting the cash flows generated in the future. The net cash flow of year t (CF_t) of a tomato glasshouse is given by:

$$NPV = -I_0 + \sum_{t=1}^{T} \frac{CF_t}{(1+r)^t} \tag{2.1}$$

where I_0 is the initial investment costs, r is the discount rate, and T is the lifetime of investment.

Based on the NPV criterion, an investment is considered economically feasible if the NPV is positive. However, glasshouse production is subject to input and output price uncertainty, leading to fluctuating cash flows. To account for the uncertainty in the glasshouse investment's financial outcome, Monte Carlo simulation was employed to calculate the stochastic cashflows and NPV.

In the Monte Carlo simulation, tomato and energy prices were modeled as stochastic variables on a monthly basis. Tomato prices directly determine the cash inflow of glasshouse production, whereas energy prices have a large impact on cash outflow as the heating costs typically account for more than 40% of production costs in China (Costa et al., 2004; Shen et al., 2018). Monte Carlo simulation consists of multiple iterations, where each iteration uses a draw from the distribution of the monthly tomato and energy prices according to the corresponding sampling strategy (see Section 2.3.4). The sampled variables of each iteration represent the possible combinations of tomato and energy prices that could occur. The NPV over the project's lifetime was calculated for each iteration. The NPV outcomes of all iterations together make up the distribution of NPV and can be used to determine the probability of a positive NPV.

2.3 **Data**

2.3.1 Initial investment costs and discount rate

The same glasshouse configuration and equipment was assumed for all four regions in China. The initial investment costs for a 1.4-hectare Venlo-type glasshouse was estimated to be ¥16.66 million (€2.22 million) (Table 2.1) The typical lifetime of a Venlo-type glasshouse is 20 years. A salvage value of zero was assumed at the end of the investment. The local government plays an important role in loan guarantee (Xiong et al., 2020). It was assumed that 50% of the initial investment is financed by a loan with an interest rate of 5.5%. A discount rate of 6.10% was then computed using the weighted average cost of capital method (see Appendix 2B).

Table 2.1. Initial investment costs for a 1.4-hectare Venlo-type glasshouse.

Items	**Cost €** $\mathbf{m^{-2}}$	**Cost €** $\mathbf{unit^{-1}}$	**Maintenance %** $\mathbf{year^{-1}}$	**Detail**
Structure	47.5 [b]		0.5% [c]	Steel structure, aluminum roof, 38% ventilation system, outside and inner walls
Cover	10.0 [a]		0.5% [c]	Roof and wall glass, insect net
Roof washer		100,000 [a]	5% [c]	
Screens	20.5 [a]		5% [c]	Outdoor shade screen, indoor thermal screen
Heating pipes	5.5 [b]		0.5% [c]	rail heating pipes and growing heating pipes
Boiler		106,700 [a]	1% [c]	
Growing gutters	14 [a]		2% [c]	Hanging gutter system
Irrigation system	5.8 [b]		5% [c]	Drip irrigation, fertilizer dosing system, water collection tank
CO2 distribution system	0.5 [a]		5% [c]	
Fogging system	3.1 [a]		5% [c]	High-pressure fogging
Pad and fan	3.7 [a]			
Electrical power system	3.3 [a]		5% [c]	Power distribution system, including wires, circuits, electric panels, etc.
Climate computer		200,000 [a]	8% [c]	Including outdoor climate monitor system and indoor climate control system
Internal transport		9,333 [a]	5% [c]	Harvest trolly (x3)
Remaining costs	6.8 [a]			Costs related to technical room, ground foil, etc.
Installation and transportation	12 [a]			Labour and transportation costs incurred for equipment installation
Total	158.7			

a. Source: investment budget of a commercial tomato glasshouse in Jinshan, Shanghai.

b. Source: Vanthoor (2012).

c. Source: Raaphorst et al. (2019).

2.3.2 Regional climate and production schedules

Hourly climate data (solar radiation, temperature, sky temperature, relative humidity, and wind speed) for each region during 1990 and 2020 was obtained from the ERA5 dataset, produced by European Centre for Medium-Range Weather Forecasts (Hersbach, H. et al., 2018). Langfang and Weifang have similar climate characteristics: abundant solar radiation, hot summer, and cold winter. Pingliang's advantage lies in its abundant solar radiation in winter and cool temperature in summer. Jinshan has mild winter, which implies lower heating demands, while it also has hot and humid summer, which significantly limits the production duration in that region. The transplant date and harvest end dates of each region were provided by a grower based on his experiences (Y. Xie, personal communication, February 6, 2022). The market prices of tomatoes are the lowest in summer due to the abundant supply of field-grown tomatoes. Moreover, the high temperature and humidity in summer limit tomato growth and is likely to induce diseases. These market and climate factors combined make summer production in Langfang, Weifang, and particularly in Jinshan, not economically feasible. The cool summer in Pingliang enables year-round production there. The starting date of the glasshouse heating was defined as the date when the outdoor temperature goes stably below 12°C, i.e., the temperature at which tomato plants suffer physiological injury (Costa & Heuvelink, 2018). The glasshouse heating end date was set as the date when outdoor temperature reaches 15°C. The detailed climate characteristics, cropping and heating schedules of the four regions can be found in Appendix 2C.

2.3.3 Gas use and yield simulation under different temperature management strategies

Climate data from 1990 to 2020 were used as inputs in the INTKAM-KASPRO model to simulate fruit yield and energy use. With 30 years of climate data, 30 runs of simulation were performed for each location. For each year of simulation, the inputs were hourly solar radiation, temperature. relative humidity, and wind speed. The yield and energy output of the year were aggregated into monthly values in further data processing.

Table 2.2 presents the mean annual yield (assuming a 5% loss rate) and mean annual gas use at different heating temperature setpoints for the four locations of the 30 runs of simulation. The standard deviations of the annual yield and natural gas use were around 0.4 kg m^{-2} and 1.1 m^3 m^{-2}, respectively, and differ slightly between locations. The indoor temperature is controlled by heating temperature setpoints, which are predetermined by growers based on their experiences. The reference setpoints were based on a commercial tomato glasshouse in Jinshan for the production cycle Oct 2019 to Jun 2020. The reference temperature setpoints were kept around 17~18℃ at daytime, and 14℃ or lower at night-time. In our simulations, the adjustment in temperature management was controlled by a temperature shift parameter. A temperature shift of −1 means to reduce the setpoints on all dates by 1℃. Accordingly, the realized indoor temperature will also decrease by approximately 1℃.

Jinshan has the lowest gas use, but also the lowest yield, presumably due to the short harvest period there. Langfang and Weifang have similar yield and energy use levels, given their similar climatic characteristics. Nevertheless, the production conditions in Weifang are slightly superior to those in Langfang, i.e., a higher yield can be expected with lower gas use in Weifang than in Langfang. The annual yield in Pingliang is substantially higher than in other regions, given the fact that the production period is seven weeks longer than in Langfang and Weifang, and 10 weeks longer than in Jinshan. The simulated gas use in Pingliang is the second lowest of all regions. The low gas use in Pingliang can be explained by the cropping schedule: transplanting starts on December 15, which means heating is only needed for half of December, one of the coldest months of the year.

Although the impacts of temperature on yield and energy use are not linear, our simulations show that a 1℃ reduction in heating setpoints (compared to the reference level) leads to a decrease in yield by around 0.5 kg m^{-2} in Jinshan, Langfang, Weifang, and by 0.8 kg m^{-2} in Pingliang. It also leads to gas savings of 2.4 m^3 m^{-2} per year in all four regions.

Table 2.2. Simulated mean tomato yield and gas use under different temperature management strategies for four regions.

TempShift	Jinshan		Langfang		Weifang		Pingliang	
	Yield kg m^{-2}	Gas use m^3 m^{-2}	Yield kg m^{-2}	Gas use m^3 m^{-2}	Yield kg m^{-2}	Gas use m^3 m^{-2}	Yield kg m^{-2}	Gas use m^3 m^{-2}
0℃ (reference)	18.01	19.54	20.37	27.24	20.57	25.60	25.07	22.45
+1℃	18.39	22.56	20.85	29.77	21.00	28.14	25.59	25.64
−1℃	17.57	17.08	19.78	24.88	20.06	23.46	24.33	20.28
−2℃	17.10	14.42	19.16	22.69	19.46	21.08	23.41	17.67

2.3.4 Parameters for stochastic price simulation

Monte Carlo simulation incorporates the information from stochastic variables to reflect the inherent risk of the investment. Tomato and energy prices were modelled as stochastic variables in the economic model, considering their large impact on the net cash flow. The biggest cost component for glasshouses in China are heating costs, taking up around 40% to 60% of the total production costs, depending on the region (Zhang, 2003). Tomato prices directly determine the revenue of the glasshouse. A commonly observed pattern in agricultural product prices is seasonality (Tomek & Kaiser, 2017).

The structural seasonal pattern in tomato prices is even more obvious because of the perishability of tomatoes. Overall, the tomato prices are lowest in summer and highest in early spring. Therefore, we model the prices of cherry tomatoes on a monthly basis. Using geometric Brownian Motion (GBM), monthly tomato prices can be described as:

$$dP_{it} = \alpha_i P_{it} dt + \sigma_i P_{it} dz \tag{2.2}$$

where P_{it} represents the tomato price of month i in year t; α_i is the drift rate; and α_i is the drift rate of month i, reflecting the expected price trend compared with the same month of the previous year. σ_i is the volatility rate, it captures price variation. ε_t is a random variable that follows the standard normal distribution. More specifically, for $t \in (0, \infty)$, P_{it} follows the lognormal distribution with parameters $\left(\alpha_i - \frac{\sigma_i^2}{2}\right) t$ and $(\sigma_i \sqrt{t})$.

The drift rate can be seen as a periodic overall inflation rate (Van den Boomen et al., 2022). Though the price series of tomatoes from 2011 to 2021 showed an upward trend, input prices (of e.g., land rent, fertilizer, wage) also increased accordingly. There was no valid underpinning to assume a positive drift rate, therefore α was set as 0. σ was estimated in the same manner as in Carey & Zilberman (2002). Tomato prices were assumed to remain in the interval [2/3P_{i0},4/3P_{i0}] with 95% probability in the next 20 years. This interval was chosen based on the observations of cherry tomato price series from 2011 to 2021. Given that the changes in $\ln P$ are normally distributed in GBM, the 90% confidence interval is given by $2 \times 1.96 \times \sqrt{20}\sigma = \ln\frac{4}{3}P_{i0} - \ln\frac{2}{3}P_{\mathrm{i}0}$, this derives a volatility rate of 0.046. The same drift and volatility rates were assumed for the four regions.

Monthly wholesale cherry tomato prices of 2021 of each region were obtained from National commercial information platform of agricultural products (nc.mofcom.gov.cn). The price data were aggregated from multiple wholesale markets in the region and did not differentiate variety and quality differences between field and glasshouse-grown tomatoes. Compared to field-grown tomatoes, glasshouse-produced tomatoes are market as high-end agri-products and can get higher prices for its better quality and brand recognition (Wang, 2020; Zhang, 2010). Therefore, a price premium of 50% was added to the aggregated wholesale tomato prices for 2021 to represent glasshouse tomato prices as the starting points (P_{i0}) for price simulation (Table 2.3). Overall, Langfang, Pingliang can expect relatively high prices for cherry tomatoes. The price of cherry tomatoes in Weifang is lower compared to other regions. The tomato price in Weifang is probably limited by the supply-demand relationship, as Shandong (where Weifang belongs to) is the largest vegetable production province in China (Costa et al., 2004).

Table 2.3. Monthly cherry tomato wholesale prices (¥ kg^{-1}) for 2021.

Month	**Jinshan**[1]	**Langfang**	**Weifang**	**Pingliang**[2]
Jan	12.00	15.23	10.86	14.01
Feb	11.18	14.60	12.99	13.43
Mar	9.62	16.91	12.66	15.56
Apr	11.03	15.93	11.12	14.66
May	13.55	14.43	9.05	13.28
Jun	11.63	12.78	6.75	11.76
Jul	11.81	11.58	8.58	10.65
Aug	12.84	11.43	9.12	10.52
Sep	14.19	11.79	9.93	10.85
Oct	15.09	12.35	11.60	11.36
Nov	17.82	17.18	12.84	15.80
Dec	18.71	17.96	13.68	16.52

Source: National commercial information platform of agricultural products (nc.mofcom.gov.cn).

Common heating energy sources are pipeline natural gas and liquid natural gas (LNG); the use of coal is restricted by law as of 2017. Our study assumes LNG as the heating energy source

[1] Cherry tomato prices of Jiangsu province were used as proxies for Jinshan cherry tomato prices due to the lack of data

[2] There are no price records for cherry tomato for Pingliang. Therefore, we estimated cherry tomato prices based on the price difference (92%) for globe tomatoes between Langfang and Pingliang.

in all four regions. LNG ex-factory prices, reflecting the average price at LNG liquefaction plants and LNG receiving stations, were obtained for each region and for 2016 to 2021 from Shanghai Petroleum and Natural Gas Exchange (SHPGX). The LNG end-user price were estimated by adding a 40% margin to the ex-factory prices. The monthly producer price data were fitted against triangular distributions using the R package *fitdistplus* (Delignette-Muller & Dutang, 2015). Six distributions of LNG prices for all heating months were obtained, the parameters are shown in Table 2.4. At each iteration of the Monte Carlo simulation, monthly natural gas prices were drawn from the fitted triangular distributions to estimate the stochastic heating costs. The natural gas prices were modelled as triangular distributions rather than geometric Brownian Motions because the trend in natural gas price is not stable over time and is difficult to predict. GMB requires a constant drift rate to reflect the stable trend in prices, while the natural gas prices in China from 2016 to 2021 fluctuated heavily. Thus, there was no reason to assign a constant drift rate to natural gas prices using GMB, as we did for tomato prices.

Table 2.4. Parameters (min, mode, max) for natural gas prices (¥ m^{-3}) simulation using triangular distributions.

Month	Jinshan[3]	Langfang	Weifang	Pingliang
Jan	2.74, 5.12, 7.01	2.36, 3.23, 8.44	2.88, 4.01, 7.01	1.76, 2.61, 9.63
Feb	3.36, 3.56, 8.33	3.04, 3.36, 6.66	3.24, 3.32, 7.25	2.68, 2.68, 7.68
Mar	3.24, 3.25, 5.14	3.06, 3.25, 4.83	3.15, 3.56, 5.37	2.90, 2.92, 4.44
Apr	2.54, 3.61, 4.20	3.05, 3.10, 4.17	2.95, 3.73, 4.39	2.70, 2.94, 4.01
Oct	2.12, 3.30, 7.95	2.68,2.94, 7.77	2.36, 3.54, 7.79	2.45, 3.35, 7.62
Nov	3.44, 3.78, 8.85	3.66, 3.75, 8.58	3.62, 3.79, 8.73	3.62, 3.73, 8.70
Dec	3.36, 3.44, 8.68	2.65, 4.35, 7.54	3.21, 3.35, 8.80	1.79, 4.25, 9.24

Note: Prices for LNG given by SHPGX are in the unit ¥ ton^{-1}. One ton of LNG was converted to 1380 m^3 of natural gas in this study.

2.3.5 Other production costs

Other production costs include labour, electricity, water, fertilizer, crop protection material, and maintenance costs. Labour hours, water use, fertilizer, pesticides, and other material costs

[3] LNG prices of Jiangsu province were used as proxies for Jinshan LNG prices due to the lack of price data for Jinshan.

were taken from data of a commercial glasshouse in Jinshan. Electricity use was an output of the KASPRO model. Labour was comprised of harvest labour that depends on tomato yield, and non-harvest labour. The latter was assumed to be the same across regions; harvest labour differs based on the yields of each region. Costs of seedlings, rockwool, fertilizers, pesticides, water, electricity, and other small items such as tomato hooks, yellow sticky traps or gloves were assumed to be the same for all regions, on the premise that the same crop management strategy was applied in the biophysical model simulation. An overview of parameters related to other production costs can be found in Appendix 2D. Information on wage and land rent of each region was obtained from the National Agricultural Products Cost-benefit Data Compilation-2020.

2.4 **Simulation results**

2.4.1 Economic performance simulation under different temperature management strategies

Table 2.5 shows Monte Carlo simulations on the net cash flow and NPV of tomato glasshouse for four regions under different temperature management strategies. The simulation consists of 1000 iterations, and the table shows the mean, 5th, and 95th percentiles of the economic indicators.

Simulations indicate that the economic feasibility of a one-hectare tomato greenhouse investment varies across regions. In Pingliang, one could expect on average a net cash flow of 143.3 ¥ m^{-2} per year. The mean NPV is 477.0 ¥ m^{-2} with a 90% confidence interval ranging from 182.0 to 749.3 ¥ m^{-2}. A one-hectare tomato glasshouse in Langfang has an average annual net cash flow of 102.0 ¥ m^{-2} and a mean NPV of 29.4 ¥ m^{-2} with a 90% confidence interval ranging from minus 301.2 to 347.8 ¥ m^{-2}. The probability of a positive NPV of a tomato glasshouse investment in Langfang is 56.8%. Results show that Jinshan and Weifang have an average annual net cash flow of 48.9 ¥ m^{-2} and 17.1 ¥ m^{-2} respectively, with the average NPV of −593.7 ¥ m^{-2} in Jinshan and −957.8 ¥ m^{-2} in Weifang. The net cash flows obtained in Jinshan and Weifang are impossible to cover the high upfront investment costs of glasshouse construction and installation, as even the 95th percentiles are negative in Jinshan and Pingliang. The major barrier in Jinshan is the short production period caused by its unfavourable local climate, which was reflected in the low simulated yield. Weifang has similar yield and gas use as Langfang, but more grim economic outcomes, due to the low tomato prices.

Table 2.5. Simulated net cash flow and NPV of tomato glasshouse under different temperature management strategies for four regions.

TempShift	Indicator	Unit	Jinshan	Langfang	Weifang	Pingliang
0°C	Mean net cash flow	¥ m^{-2} $year^{-1}$	48.9	102.0	17.1	143.3
	Mean NPV	¥ m^{-2}	−593.7	**29.4**	−957.8	**477.0**
	5% NPV	¥ m^{-2}	−829.4	−301.2	−1231.0	182.0
	95%NPV	¥ m^{-2}	−355.5	347.8	−705.0	749.3
+1°C	Mean net cash flow	¥ m^{-2} $year^{-1}$	44.5	102.9	15.9	140.5
	Mean NPV	¥ m^{-2}	−654.1	10.8	−1018.3	439.2
	5% NPV	¥ m^{-2}	−902.5	−334.8	−1302.5	123.7
	95% NPV	¥ m^{-2}	−398.2	343.9	−749.2	728.6
−1°C	Mean net cash flow	¥ m^{-2} $year^{-1}$	54.0	104.3	23.8	138.3
	Mean NPV	¥ m^{-2}	−546.1	26.5	−888.8	472.3
	5% NPV	¥ m^{-2}	−768.6	−284.5	−1147.1	194.2
	95% NPV	¥ m^{-2}	−327.0	331.0	−647.5	727.0
−2°C	Mean net cash flow	¥ m^{-2} $year^{-1}$	57.9	103.7	24.4	139.8
	Mean NPV	¥ m^{-2}	**−501.1**	19.8	**−875.1**	430.7
	5% NPV	¥ m^{-2}	−707.6	−267.4	−1112.7	174.2
	95% NPV	¥ m^{-2}	−300.7	310.6	−644.8	671.8

2.4.2 Sensitivity analysis

A sensitivity analysis helped to determine which factors have a major impact on the net cash flow of a tomato glasshouse. A regression-based sensitivity analysis procedure was applied by regressing the ranked net cash flow against the ranked monthly tomato and natural gas prices. Table 2.6 shows the standardized regression coefficients between the ranked net cash flow and the ranked monthly tomato and natural gas prices. The larger the regression coefficient, the more closely the variation in the price variable is associated with the net cash flow. Overall, the impact of natural gas prices variation on the net cash flow was higher than tomato prices. For Jinshan and Langfang, tomato prices from May and June have large impacts on the net cash flow. For Weifang, tomato prices from March to May and December have the largest impacts on net cash flow. In Pingliang, the most influential months for tomato prices are April, November, July, and August. Not surprisingly, the cold months, December, January, and February are when natural gas prices have the largest impact on net cash flow for all regions.

Table 2.6. Standardized regression coefficients between the ranked net cash flow and the ranked monthly tomato and natural gas prices.

Variable	Jinshan	Langfang	Weifang	Pingliang
Tomato prices				
Jan	0.15	0.11	0.09	n/a
Feb	0.13	0.09	0.10	n/a
Mar	0.09	0.12	0.11	0.07
Apr	0.14	0.15	0.12	0.17
May	0.22	0.16	0.11	0.12
Jun	0.19	0.15	0.09	0.09
Jul	n/a	(0. 02)	(0.01)	0.13
Aug	n/a	n/a	n/a	0.13
Sep	n/a	n/a	n/a	0.11
Oct	n/a	n/a	n/a	0.11
Nov	n/a	(0.01)	(0.02)	0.15
Dec	0.14	0.13	0.11	0.06
Natural gas prices				
Jan	−0.48	−0.66	−0.47	−0.29
Feb	−0.50	−0.28	−0.36	−0.28
Mar	−0.17	−0.10	−0.14	−0.12
Apr	−0.07	−0.02	−0.03	−0.06
Oct	n/a	−0.02	n/a	−0.29
Nov	n/a	−0.32	−0.30	−0.21
Dec	−0.56	−0.48	−0.65	−0.45

Notes: statistically insignificant coefficients ($p>0.05$) are reported in parenthesis. n/a indicates a month without yield or natural gas use.

2.4.3 Scenario analysis

Producers have no control over tomato and gas prices, while these two factors significantly affect both revenue and heating costs. A scenario analysis was conducted to analyse what the tomato and natural gas prices should be in order to make the investment break even (mean NPV=0). Local governments in China usually provide substantial subsidies to support glasshouse investments. The subsidy policies vary from province to province. In the scenario analysis, both scenarios with (50% of the initial investment cost) and without subsidy were assessed. The baseline scenario was the economic outcome under the grower reference temperature setpoints. The scenario analysis of Pingliang is presented here (Figure 2.2). Detailed results for other regions are in Appendix 2E.

Pingliang is the region with the most optimistic economic outcome among the four regions. The Without subsidy, the break-even tomato prices are 86.9% of the current tomato prices, given the current natural gas prices unchanged. With a subsidy of 50% of the initial investment costs, even if the tomato prices decrease by 29.2%, glasshouse investment in Pingliang can still break-even. Given the current tomato prices, the investment can tolerate an increase in natural gas prices by 41.9%. When a subsidy of 50% of the initial investment costs is available, glasshouse in Pingliang can still make a positive NPV even if the natural gas prices increase by 93.4%.

Pingliang: NPV (¥ m^{-2}, without subsidy)

Percent change in natrual gas prices \ Percent change in cherry tomato prices	-40%	-20%	0%	20%	40%	60%	80%
-40%	-519.0	201.4	921.9	1642.3	2362.8	3083.2	3803.6
-20%	-744.0	-23.6	696.9	1417.3	2137.8	2858.2	3578.7
0%	-969.0	-248.5	477.0	1192.3	1912.8	2633.2	3353.7
20%	-1194.0	-473.5	246.9	967.3	1687.8	2408.2	3128.7
40%	-1419.0	-698.5	21.9	742.4	1462.8	2183.2	2903.7
60%	-1644.0	-923.5	-203.1	517.4	1237.8	1958.2	2678.7
80%	-1869.0	-1148.5	-428.1	292.4	1012.8	1733.3	2453.7

Pingliang: NPV (¥ m^{-2}, 50% subsidy of intital investment)

Percent change in natrual gas prices \ Percent change in cherry tomato prices	-40%	-20%	0%	20%	40%	60%	80%
-40%	60.2	780.7	1501.1	2221.6	2942.0	3662.5	4382.9
-20%	-164.7	555.7	1276.1	1996.6	2717.0	3437.5	4157.9
0%	-389.7	330.7	1051.1	1771.6	2492.0	3212.5	3932.9
20%	-614.7	105.7	826.2	1546.6	2267.0	2987.5	3707.9
40%	-839.7	-119.3	601.2	1321.6	2042.0	2762.5	3482.9
60%	-1064.7	-344.3	376.2	1096.6	1817.1	2537.5	3257.9
80%	-1289.7	-569.3	151.2	871.6	1592.1	2312.5	3032.9

Figure 2.2. Mean NPV of a 1.4-hectare tomato glasshouse under different tomato and gas price.

2.5 **Discussion**

The objective of this study was to analyse the economic feasibility and uncertainty of a Venlo-type glasshouse for tomato production in China, under different climatic and market conditions. This interdisciplinary study combined methodologies from different disciplines such as greenhouse engineering, crop management, and economics and explored the dependencies between outdoor climate, management decisions on greenhouse climate, yield, and economic feasibility of a glasshouse production system for tomatoes in China. The results show that the economic outcome of a tomato glasshouse varies across regions, with a mean NPV ranging from for −957.8 ¥ m^{-2} Weifang, to 477.0 ¥ m^{-2} for Pingliang. The 5th and 95th percentiles of NPV of a tomato glasshouse investment in Pingliang are 182.0 and 749.3 ¥ m^{-2}, respectively. Such investment is unlikely to be profitable in Jinshan and Weifang. The probability of a positive NPV of a tomato glasshouse investment in Langfang is 56.8%. We also simulated the economic outcomes of tomato glasshouse under different temperature setpoints for each region. The highest mean NPVs in Langfang and Pingliang were obtained at the grower's reference setpoints. In Jinshan and Weifang, higher NPV can be obtained by decreasing the reference setpoints by 2 ℃, at the expense of some yield reduction. A sensitivity analysis was conducted to evaluate the risks associated with the tomato and natural gas prices. The break-even tomato and natural gas prices for each region were calculated with a scenario analysis.

The reasons that glasshouse investments in Jinshan and Weifang are unprofitable are multifold: first, the short production cycle limits yield levels. In Jinshan, the production duration is only 39 weeks, in contrast to the Netherlands where 50 weeks of production is possible. The annual yield of cherry tomato in the Netherlands is around 30.7 kg m^{-2}, while the yield in Jinshan is only 18.01 kg m^{-2}. Second, cherry tomato prices in China are relatively low (1.2 to 3.2 € kg^{-1}), compared to for example the Netherlands (1.63 to 5.77 € kg^{-1}; Raaphorst et al., 2019). Meanwhile, natural gas prices in China are relatively high (0.5 to 0.7 € m^{-3}). In the Netherlands, the natural gas price is around 0.24 € m^{-3} (Raaphorst et al., 2019) and in Norway 0.43 € m^{-3} (Naseer, et al., 2022b). The negative impacts of high natural gas price are not only reflected in the high heating costs, but also in the low yield levels in China. Being able to operate throughout the year, Pingliang's simulated yield was around 25 kg m^{-2}, nearly 6 kg m^{-2} lower than the yield in the Netherlands. The low yield can be partly explained by the low temperature setpoints set by Chinese growers for saving heating costs.

The sensitivity analysis suggests that both tomato and natural gas prices play decisive roles in the profitability of glasshouse investment. In China, there is a clear trend that commercial glasshouses are spending more resources on branding, seeking to exercise market power and get price premium through brand recognition. By improving quality management and establishing direct contracts with high-end supermarkets or online market access to consumers, glasshouse-produced tomatoes may have a chance to obtain a price premium. The grower could also strategically choose tomato varieties that cater to specific market segments and get a higher revenue. For example, beef tomato can reach a much higher yield compared to cherry tomato, but the price of beef tomato is usually lower. It is thus a strategic decision for the grower to choose the tomato variety that brings the highest return.

The sensitivity analysis also suggests that the impact of natural gas prices was much bigger than that of tomato prices. Natural gas price variations could impose a lot of uncertainty to glasshouse investments. China's natural gas market greatly depends on import. In recent years, energy prices are mounting and becoming even more volatile. Building long-term contracts with energy suppliers is a way to reduce cost uncertainty. However, energy suppliers tend to only establish contracts with large buyers, but the LNG demand of a 1.4-hectare glasshouse is below 200 tons per year. The use of pipeline gas, which is to some extent regulated by the government and therefore less volatile and slightly cheaper, could decrease the uncertainty about net cash flow. However, the prerequisite is that the glasshouse has connections to pipeline gas. The cost for pipeline construction can be as high as one million RMB per kilometre (K. Yang, personal communication, October 21, 2020). Agricultural infrastructure access is an important success factor for the development of modern agriculture in China.

Some literature on greenhouse temperature optimization followed the principle of energy-efficiency of biomass production (e.g., Luo et al., 2005a) or simply optimized the daily temperature setpoints based on a given desired average temperature (e.g., Shen et al., 2018). Without taking the prices of agricultural products and energy into account, these perspectives do not necessarily lead to the economic optimum results. What investors ultimately care about is the profitability of the glasshouse. In this regard, including outputs and energy prices and follow the profit-maximization principle is a more appropriate guideline for glasshouse temperature optimization. After including fixed tomato and energy prices, Su et al. (2021) recommended the temperature setpoints of a Venlo-type tomato glasshouse in Shanghai in winter to be between 16 to 20℃. After considering seasonality and uncertainty of tomato and energy prices, our study suggests that better economic outcome can be obtained by lowering the temperature by 2℃ compared to the reference setpoints, which led to an average temperature around 15℃.

Crop and greenhouse climate models have been used extensively as tools to study the dynamics of crop growth and development and the indoor greenhouse climate. Linking such bio-physical models with economic models is a way forward toward more integrated assessments of agricultural systems (Lehmann, N., 2013). Without simplifying the dependencies between outdoor climate, energy use, and tomato yield, this paper is the first to systematically assess the economic feasibilities of glasshouse investments in China, to the best of our knowledge. this study provides the distribution of possible economic outcomes which is helpful for investment risk assessment. By revealing the trade-offs between yield and heating costs, our study appeals to adhere to the principle of profit maximization when formulating glasshouse climate management strategies. This paper is interdisciplinary in nature by integrating knowledge from crop physiologists, greenhouse energy experts, agricultural economists, and glasshouse practitioners.

There are, however, some limitations of this study that need further discussion. First, when exploring different heating temperature setpoints, we assumed that temperature only affects the yield and natural gas use. In fact, temperature also influences tomato quality, such as fruit colour, texture, and size (Dorais et al., 2010). The impact of temperature management on fruit quality was not modelled in this study, as this is beyond the scope of our biophysical model.

Second. this study only considered Venlo-type glasshouses, a type of high-tech greenhouses with a complete set of climate control equipment. Although this Venlo-type glasshouse was found to be unprofitable in some regions under the current conditions, other types of greenhouses with different designs and technological levels may be economically viable in China. Future research can compare the economic feasibilities of different types of greenhouses and explore the most economic viable greenhouse design under different climate regions in China. Similar studies have been done for Spain (Vanthoor et al., 2012) and Norway (Naseer et al., 2021), but have not been done in China. This could be done with our modelling framework, with some modifications on the definition of glasshouse configuration. Another future research direction is to incorporate the yield and energy use uncertainty caused by the variations of the outdoor climate. This study used the mean yield and energy use simulated with 30 historical climate datasets as deterministic values in the calculation. The standard deviations of 30 years simulated yield and natural gas use were around 0.4 kg m^{-2} and 1.1 m^3 m^{-2} respectively, which could bring some extra uncertainty in the economic outcome of glasshouse investment. Incorporating uncertainty caused by climate variations can enable a more complete view of the uncertainty of glasshouse investment.

This study used historical climate data in the bio-economic simulation to assess the economic feasibility of a future investment. It would be ideal to use climate projections as input for yield and energy use simulation to match the investment decision horizon. The effect of climate change on agricultural production is gaining attention in the literature. A review indicated that the changing temperature, CO_2 concentration and precipitation patterns may have positive and negative impacts on different aspects of greenhouse production (Gruda et al., 2019). Many impacts of climate change on greenhouse production discussed in the literature were concluded from studies of vegetables grown under adverse climate conditions, and simulation studies on this topic are scarce (Gruda et al., 2019). A future research opportunity is to study the influence of climate change on greenhouse production with bio-economic models using future climate projections.

Different climate and crop management strategies can also be studied with this modelling framework. In this paper, we explored the economic outcomes under four different levels of heating temperature setpoints and revealed the trade-offs between yield and heating costs. This is nevertheless a simplified temperature setpoints optimization procedure. In future work, climate management and crop management (e.g., pruning, leaf removal) strategies could be optimized simultaneously to reach the profit-maximizing point for different regions in China.

Local governments play an important role in the development of the glasshouse industry in China. In fact, local governments are not only subsidy providers but also joint investors of glasshouse projects. Normally, the government would claim part of the glasshouse's ownership based on the portion of subsidy they provided. The local government also plays an important role in financing, by helping the private investors to negotiate with banks for favourable loan terms. With a subsidy of 50% of the initial investment costs, the probability of a tomato glasshouse with a positive NPV can increase to 46.4% in Jinshan and 99.9% in Langfang. Currently, the subsidy is often given as a fixed amount paid as a proportion of the initial investment costs, usually paid off within three years after the glasshouse is built. The governments could diversify the forms of subsidy. Apart from fixed one-time payments, the government could consider giving annual subsidies on glasshouse production, such as energy price subsidy, to ensure that the glasshouses can produce sustaining cash flows.

For a long time, glasshouse technology R&D has focused on energy-saving heating technologies. This is very relevant in countries with cool summers, for example the Netherlands. Indeed, heating is a large cost component, but given the climate characteristics in China (hot and humid summer), it seems to be more worthwhile to put more effort into developing energy-efficient cooling and dehumidification technologies to enable glasshouse production throughout the year. With a prolonged production period, the revenue could be substantially increased, as can be seen from the simulation results of Pingliang.

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Declaration of interest statement

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Appendix 2A. INTKAM and KASPRO models calibration results

We employed the INTKAM-KASPRO model[4] to simulate yield and energy use of a Venlo-type glasshouse in which tomato crop was grown, for the economic feasibility studies of four different regions in China. The model was calibrated to ensure reasonable simulation results for Chinese production situations. We used the production data from year 2019 and 2020 of a cherry tomato glasshouse in Jinshan, Shanghai (latitude 30.8173° N, longitude 121.0410° E). Details on the structure, equipment climate and crop management strategies of the Jinshan glasshouse can be found in Table A1. Table A2 and A3 presents the calibration results on yield and energy use of the INTKAM-KASPRO model under the Shanghai climate.

Table A1. Actual information of the glasshouse in Jinshan and the parameters used for model calibration.

Item	**Actual information**	**Description**
Area	8000 m^{-2}	✓
Gutter height	6.5 m	✓
Orientation	EW, 0 degree	✓
Cover	Normal glass, no whitewash	✓
Heating	Boiler (liquid natural gas), no heat storage; Two heating pipes	maximum supply temperature of heating pipes: 60°C for pipe1, 50°C for pipe 2.
Screens	Thermal screen + shading screen	The thermal screens may be used when the outside temperature is below 12°C. When the outside temperature goes below 0°C, the thermal screen will be kept deployed until the radiation is above 200 w m^{-2}. When the outside temperature is above 10°C, the thermal screen is only closed when the radiation is below 5 w m^{-2}. The shading screen will be half closed when the radiation exceeds 600 w m^{-2} and fully closed when the radiation exceeds 800 w m^{-2}.

[4] The KASPRO simulation model is based on physical equations that describe the heat and mass fluxes associated with greenhouse plant production. It dynamically simulates the greenhouse temperature, relative humidity, transpiration, etc. and calculates the energy and CO_2 uses based on the given greenhouse climate setpoints. The INTKAM model simulates growth and development of greenhouse crops (in our case, tomato). Crop photosynthesis rate is computed at small time steps with a biochemical model on the basis of radiation, CO_2, temperature, and relative air humidity. Instantaneous rates are integrated to a daily crop photosynthesis rate. Daily dry matter partitioning and organ growth rates are computed based on the sink strengths of various organs and assimilate availability.

Cooling	Pad & fan, fogging. No dehumidification	The maximum amount of outside air sucked in is 100 m3 m^{-2} h^{-1}. The fans will run on the maximum capacity when the difference between the air-temperature and ventilation setpoint excesses 2°C. The air can be cooled down to 0.85 of the wet-bulb temperature. The outlet temperature is 15°C above the average greenhouse temperature.
Illumination	No	✓
Heating period	11/29/2019 – 04/23/2020	✓
Heating setpoints	No data	Inferred from realized indoor temperature
Ventilation setpoints	No data	The maximum opening of vents is 100. When the outside temperature is below 5°C, the p-band is 15°C; when the outside temperature is higher than 20°C, the p-band is 4°C. p-band is a key parameter that controls how large the temperature excess has to be before the leeward vents are fully opened. The windward vents only open when the leeward vents are opened above 50%.
CO_2	Censor data, mean CO_2=550 ppm	✓
Transplant date	10/01/2019	✓
Stem density	2.06 (10/01/2019) 2.58 (since 10/22/2019)	✓
Topping date	05/20/2020	✓
Last harvest date	03/06/2020	✓
Nr. fruit per truss	Initially 8, reduced to 6 and increased to 8 eventually	Fruit number per truss was calibrated accordingly
Dry matter content	5%–7%, depend on the development stage. Eventually stabilized around 6%	Dry matter content was set at 6%

Note: ✓ means that the underlying parameter reflects the exact glasshouse specification, climate or crop management strategies in the actual production

Simulated yield was 2.63 kg m^{-2} higher than actual yield. The over-estimation can be explained by the fact that the model assumes absence of pests and diseases, optimal fertigation management and other crop management actions, which, however, is unlikely to be achieved in practical production, especially the Jinshan glasshouse data was obtained from an experimental cultivation. Many operators were interns without working experience in glasshouses. In addition, some abnormal events during the production cycle 2019-2020:

- In March, some work (leaf removal, harvest, side shoot removal) could not be finished in time due to labour shortage during the covid-19 pandemic.
- In April, powdery mildew and leaf mold appeared.
- Towards the end of harvest, blossom end rot appeared on three trusses.

For these reasons, the model was considered to realistically simulate the tomato production in Jinshan.

Table A2. Summary of simulated and actual harvest.

Yield kg m^{-2} $year^{-1}$	**Actual**	**Simulation**
Dec	1.727	1.933
Jan	2.121	2.859
Feb	1.209	1.908
Mar	1.433	2.005
Apr	3.106	2.989
May	3.321	4.160
Jun	0.634[5]	0.325
Total	13.55	16.18

Gas use was over-estimated. The simulated gas use was 12.2 m^3 m^{-2}, the adjusted actual gas use (after linearly extrapolates 12 missing values) was 12.82 m^3 m^{-2}. One explanation is that the energy use information provided by the grower was inaccurate, for example, there were missing values in the daily gas use record. Overall, the daily gas use pattern has the same trend as the actual use pattern, therefore we decided to accept this slight over-estimation and put more trust in the widely validated model.

Electricity use was under-estimated, because the simulated electricity use only took large electricity consumption equipment into account (e.g., heat pumps, pad and fan systems, air-

[5] The actual harvest in June was 1.563 kg m^{-2}, including green fruits without commercial value. We only took the harvested red fruit weight into account for calibration, as the green fruit were the fruits supposed to be harvested in later stage beyond the simulation period. The Jinshan greenhouse ended the production already on June 3 to avoid high cooling costs and diseases brought by the hot and humid climate in summer.

blower of the boiler). Smaller consumers of electricity, like circulation fans, watering pumps, pumps for circulating water in the heating system were not included. While the actual electricity use most likely takes every consumption into account. As the electricity costs only takes up around 5% of the total production costs, this over-estimation will have a minor effect on the cost estimation, which is acceptable.

Table A3. Summary of the actual and simulated energy use for the Jinshan glasshouse.

Item	**Value per year**
Actual gas use	12.2 m^3 m^{-2}
Adjusted actual gas use	12.82 m^3 m^{-2}
Simulated gas use	15.5 m^3 m^{-2}
Actual electricity use (everything included)	7.3 kWh m^{-2}
Actual electricity use (only for glasshouses)	5.67 kWh (estimation, 70%*8.1)
Simulated electricity use (only for heat pumps, air-blower of boiler, cooling)	4.3 kWh

Appendix 2B. Calculation of weighted average cost of capital (WACC)

Table B1. Calculation of weighted average cost of capital.

Cost of debt after tax shield (CD)	**Rate**	**Source**
Cost of debt (Rd)	5.5%	The People's Bank of China (2022), with the assumption of 20% floating rate on the 5-year Loan Prime Rate of 2022 (4.6%)
Marginal tax rate (T)	0.0%	Enterprise Income Tax Law of the People's Republic of China, article 27 (2007)
Cost of debt after tax shield	5.5%	
Cost of equity (CE)		
Risk free rate (rfr)	2.79%	China 10-year government bond yield (Ministry of Finance of the People's Republic of China, 2022)
Market risk premium of China (rm)	4.94%	(Damodaran, 2022a)
Beta for farming sector in China (β)	0.79	(Damodaran, 2022b)
Cost of equity	6.69%	Calculated
Capital structure	Ratio	
Debt (D)	50%	Authors' assumption
Equity (E)	50%	Authors' assumption
WACC	6.10%	Calculated

The discount rate r was calculated using the WACC method as follows:

$$r = WACC = \frac{D}{D+E} \cdot CD + \frac{E}{D+E} \cdot CE = \frac{D}{D+E} \cdot Rd \cdot (1-T) + \frac{E}{D+E} \cdot (rfr + \beta \cdot rm)$$

Appendix 2C. Climate characteristics, cropping and heating schedules of four regions

Table C1. Climate characteristics, cropping and heating schedules of four regions.

	Jinshan	Langfang	Weifang	Pingliang
Longitude	30°49'51.96" N	39°30'34.99" N	36° 42' 24.39" N	35°32'21.01" N
Latitude	121°20'38.40" E	116°41'40.99" E	119° 9' 42.33" E	106°41'10.00" E
Gross radiation of the year (MJ m^{-2})	5383.1	5728.5	5734.5	5586.4
Gross radiation in Dec, Jan, Feb (MJ m^{-2})	843.2	867.0	879.2	933.6
Average temperature in Jan (°C)	6.03	−3.05	−1.24	−2.94
Average temperature in Jul (°C)	28.05	27.63	26.64	22.63
Average humidity in Jul (%)	83.59	70.18	75.54	67.67
Transplanting date	Oct 1	Sep 15	Sep 15	Jan 1
Heating start date	Dec 1	Oct 25	Nov 5	Oct 10
Heating end date	Apr 20, next year	Apr 13, next year	Apr 20, next year	Apr 30
Final harvest date	Jul 1, next year	Jul 10, next year	Jul 10, next year	Dec 15
Weeks of production	39	43	43	50

Appendix 2D. Overview of parameters related to other production costs

Table D1. Parameters related to other production costs.

Parameter	Unit	Values
Natural gas use [a]	$m^3\ m^{-2}\ month^{-1}$	See Table 2.2
Electricity use [a]	$kWh\ m^{-2}\ month^{-1}$	Jinshan: 7.24 Langfang: 7.43 Weifang: 7.56 Pingliang: 6.23
Wage [b]	¥ $hour^{-1}$	Jinshan: 16.9 Langfang: 13.3 Weifang: 11.5 Pingliang: 9.35
Harvest labour hour [c]	$hour\ kg^{-1}\ year^{-1}$	0.032
Non-harvest labour hour [c]	$hour\ m^{-2}\ year^{-1}$	0.64
Land rent [b]	¥ $m^{-2}\ year^{-1}$	Jinshan: 1.06 Langfang: 0.63 Weifang: 0.58 Pingliang: 0.50
Water [c]	¥ m^{-2}	3.33
Electricity [c]	¥ kWh^{-1}	0.682
Fertilizers [c]	¥ $m^{-2}\ year^{-1}$	7.15
Rockwool [c]	¥ $m^{-2}\ year^{-1}$	11.88
Seedlings [c]	¥ $m^{-2}\ year^{-1}$	1.38
Other material [c]	¥ $m^{-2}\ year^{-1}$	3.26

a. Source: simulation outputs of INTKAM-KASPRO model

b. Source: National Agricultural Products Cost-benefit Data Compilation-2020 (2020)

c. Source: accountancy data from a cherry tomato glasshouse in Jinshan

Appendix 2E. Scenario analysis results and break-even prices

Jinshan: NPV (¥ m^{-2}, without subsidy)

Percent change in natrual gas prices \ Percent change in cherry tomato prices	-40%	-20%	0%	20%	40%	60%	80%
-40%	-1201.7	-694.6	-187.6	**319.5**	**826.6**	**1333.6**	**1840.7**
-20%	-1408.9	-901.8	-394.7	**112.3**	**619.4**	**1126.4**	**1633.5**
0%	-1616.0	-1109.0	-593.7	-94.9	**412.2**	**919.3**	**1426.3**
20%	-1823.2	-1316.2	-809.1	-302.0	**205.0**	**712.1**	**1219.2**
40%	-2030.4	-1523.3	-1016.3	-509.2	-2.2	**504.9**	**1012.0**
60%	-2237.6	-1730.5	-1223.5	-716.4	-209.3	**297.7**	**804.8**
80%	-2444.8	-1937.7	-1430.6	-923.6	-416.5	**90.6**	**597.6**

Jinshan: NPV (¥ m^{-2}, 50% subsidy of intital investment)

Percent change in natrual gas prices \ Percent change in cherry tomato prices	-40%	-20%	0%	20%	40%	60%	80%
-40%	-622.4	-115.4	**391.7**	**898.7**	**1405.8**	**1912.9**	**2419.9**
-20%	-829.6	-322.6	**184.5**	**691.6**	**1198.6**	**1705.7**	**2212.8**
0%	-1036.8	-529.7	-22.7	**484.4**	**991.5**	**1498.5**	**2005.6**
20%	-1244.0	-736.9	-229.8	**277.2**	**784.3**	**1291.3**	**1798.4**
40%	-1451.2	-944.1	-437.0	**70.0**	**577.1**	**1084.2**	**1591.2**
60%	-1658.3	-1151.3	-644.2	-137.1	**369.9**	**877.0**	**1384.0**
80%	-1865.5	-1358.4	-851.4	-344.3	**162.7**	**669.8**	**1176.9**

Figure E1. Mean NPV of a 1.4-hectare tomato glasshouse under different tomato and gas price changes for Jinshan, without and with 50% subsidy on the initial investment costs.

Langfang: NPV (¥ m^{-2}, without subsidy)

Percent change in natrual gas prices \ Percent change in cherry tomato prices	-40%	-20%	0%	20%	40%	60%	80%
-40%	-811.4	-112.9	**585.7**	**1284.3**	**1982.8**	**2681.4**	**3380.0**
-20%	-1094.2	-395.6	**302.9**	**1001.5**	**1700.1**	**2398.6**	**3097.2**
0%	-1377.0	-678.4	**29.4**	**718.7**	**1417.3**	**2115.9**	**2814.4**
20%	-1659.7	-961.2	-262.6	**436.0**	**1134.5**	**1833.1**	**2531.7**
40%	-1942.5	-1243.9	-545.4	**153.2**	**851.8**	**1550.3**	**2248.9**
60%	-2225.3	-1526.7	-828.1	-129.6	**569.0**	**1267.6**	**1966.1**
80%	-2508.0	-1809.5	-1110.9	-412.3	**286.2**	**984.8**	**1683.4**

Langfang: NPV (¥ m^{-2}, 50% subsidy of intital investment)

Percent change in natrual gas prices \ Percent change in cherry tomato prices	-40%	-20%	0%	20%	40%	60%	80%
-40%	-232.2	**466.4**	**1165.0**	**1863.5**	**2562.1**	**3260.7**	**3959.2**
-20%	-515.0	**183.6**	**882.2**	**1580.8**	**2279.3**	**2977.9**	**3676.5**
0%	-797.7	-99.2	**599.4**	**1298.0**	**1996.5**	**2695.1**	**3393.7**
20%	-1080.5	-381.9	**316.6**	**1015.2**	**1713.8**	**2412.3**	**3110.9**
40%	-1363.3	-664.7	**33.9**	**732.4**	**1431.0**	**2129.6**	**2828.1**
60%	-1646.0	-947.5	-248.9	**449.7**	**1148.2**	**1846.8**	**2545.4**
80%	-1928.8	-1230.2	-531.7	**166.9**	**865.5**	**1564.0**	**2262.6**

Figure E2. Mean NPV of a 1.4-hectare tomato glasshouse under different tomato and gas price changes for Langfang, without and with 50% subsidy on the initial investment costs.

Weifang: NPV (¥ m^{-2}, without subsidy)

Percent change in natrual gas prices \ Percent change in cherry tomato prices	-40%	-20%	0%	20%	40%	60%	80%
-40%	-1391.4	-904.4	-417.4	**69.6**	**556.6**	**1043.6**	**1530.6**
-20%	-1664.5	-1177.5	-690.5	-203.5	**283.5**	**770.5**	**1257.5**
0%	-1937.7	-1450.7	-957.8	-476.6	**10.4**	**497.4**	**984.4**
20%	-2210.8	-1723.8	-1236.8	-749.8	-262.8	**224.2**	**711.2**
40%	-2483.9	-1996.9	-1509.9	-1022.9	-535.9	-48.9	**438.1**
60%	-2757.1	-2270.1	-1783.1	-1296.0	-809.0	-322.0	**165.0**
80%	-3030.2	-2543.2	-2056.2	-1569.2	-1082.2	-595.2	-108.2

Weifang: NPV (¥ m^{-2}, 50% subsidy of intital investment)

Percent change in natrual gas prices \ Percent change in cherry tomato prices	-40%	-20%	0%	20%	40%	60%	80%
-40%	-812.1	-325.1	**161.9**	**648.9**	**1135.9**	**1622.9**	**2109.9**
-20%	-1085.3	-598.3	-111.3	**375.7**	**862.7**	**1349.8**	**1836.8**
0%	-1358.4	-871.4	-384.4	**102.6**	**589.6**	**1076.6**	**1563.6**
20%	-1631.5	-1144.5	-657.5	-170.5	**316.5**	**803.5**	**1290.5**
40%	-1904.7	-1417.7	-930.7	-443.7	**43.3**	**530.3**	**1017.4**
60%	-2177.8	-1690.8	-1203.8	-716.8	-229.8	**257.2**	**744.2**
80%	-2451.0	-1963.9	-1476.9	-989.9	-502.9	-15.9	**471.1**

Figure E3. Mean NPV of a 1.4-hectare tomato glasshouse under different tomato and gas price changes for Weifang, without and with 50% subsidy on the initial investment costs.

Table E1. Break-even tomato and natural gas price levels of the four regions.

Break-even	**Without subsidy**	**50% subsidy**
Break-even tomato price level		
Jinshan	23.7%	0.9%
Langfang	-0.6%	-17.2%
Weifang	39.6%	15.8%
Pingliang	-13.1%	-29.2%
Break-even natural gas price level		
Jinshan	-58.1%	−2.2%
Langfang	1.43%	42.4%
Weifang	-70.6%	−28.2%
Pingliang	41.9%	93.4%

Notes: break-even tomato (natural gas) price level refers to the percent change in the current tomato (natural gas) prices to make the glasshouse investment break even (mean NPV=0), keeping the current natural gas (tomato) prices level unchanged.

Chapter 3 Multi-stakeholder multi-objective greenhouse design optimization in China

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Abstract

Optimizing greenhouse design is a complex challenge that involves the large combinational solution space and the interactions between design elements, outdoor climate, and crops. In addition, evaluating greenhouse performance requires consideration of economic and environmental dimensions, as well as different stakeholder priorities. To address this challenge, this paper made a novel combination of operational research methods with bio-economic modelling. Specifically, a bio-economic model was used to simulate the yield, energy use, and economic performance of different greenhouse designs. A genetic algorithm was used to explore the large solution space to reduce the computational effort. The overall performance of greenhouse design was evaluated using a directional distance function, which incorporated stakeholders' priorities for economic and environmental performance through the directional vector. The results identify several greenhouse designs that were found to be efficient in terms of economic and environmental performance for both investors and policymakers across various price scenarios. The most influential factors on operating income include the choice of lighting, structure, thermal screen, and CO_2 dosing rate. Among lighting options, LED lighting outperforms HPS lighting in terms of both economic and environmental performance. Specifically, incorporating LED lamps with an intensity of 200 μmol m^{-2} s^{-1} can increase annual operating income by 97.3 to 200.2 ¥ m^{-2}, depending on the region. Conversely, low intensity lighting adversely impacts both economic and environmental performance. A synergistic relationship has been observed between lighting and CO_2 dosing. On the other hand, lighting is the primary contributor to greenhouse gas (GHG) emissions. Incorporating LED lighting with an intensity of 200 μmol m^{-2} s^{-1} can increase CO_2 equivalent emissions from 151.7 to 211.0 kg m^{-2}. Incorporating thermal screens can effectively reduce GHG emissions.

Keywords

Greenhouse design, Data envelopment analysis, Genetic algorithm, Bio-economic model, Multi-stakeholder

3.1 Introduction

China has the largest area of protected horticulture in the world, covering 1.89 million hectares (ha) by 2018 (Sun et al., 2019). However, China's protected horticulture is dominated by Chinese solar greenhouses[6] (66.6%) and single-span plastic tunnels (30.5%), which are typically small in size and have limited climate control capabilities. In comparison, large-scale modern greenhouse such as multi-tunnel plastic greenhouses or Venlo-type glasshouses, only make up 2.9% of China's protected horticulture area.

Promoting agricultural mechanization has become as a top priority of the Ministry of Agriculture (MOA) in China. Subsidies have stimulated a surge in investment in Venlo-type glasshouse in China (MOA, 2018). However, the economic returns of these investments were questionable (MOA, 2018). One explanation may be that the designs of these greenhouses were often imported directly from countries such as the Netherlands, without sufficient adaptation to the local climatic and market conditions in China. Identifying greenhouse designs that are optimally adapted to the local climate and market conditions in China is currently of high policy relevance.

Existing studies on greenhouse designs mostly address the design as a single factorial problem (e.g., Luo et. al., 2005b; Wang et. al., 2014; Esmaeli & Roshandel, 2020), i.e., by optimizing one design element at a time. However, the design of greenhouse production systems is clearly a multi-factorial optimization problem (van Henten et al., 2006), requiring the selection of the best combination of design elements, such as the structure and cover material, the choice of heating system, screens, CO_2 supply, and artificial lighting. All of these choices mutually influence each other and are affected by local climate and market conditions (van Henten et al., 2006). A recent stream of literature advocates a more systematic approach, i.e., integrating the physical, biological, and economic models, and optimizing multiple factors simultaneously (e.g, Vanthoor et al., 2012; Naseer et al., 2021).

One of the methodological challenges of taking a systematic approach is the "curse of dimensionality"—the number of possible combinations increases exponentially with the number of design elements and the number of alternatives of each design element.

[6] The Chinese solar greenhouse features an arc-shaped south-facing, light-transmitting roof, and an energy-storing north wall. During the day, solar energy is collected through the roof and stored in the north wall and soil. The stored energy is released at night, with a thermal blanket applied to prevent energy loss. No additional heating is applied this type of greenhouse (Montero et al., 2019).

Consequently, selecting the best combination of design options can be a complex task. Vanthoor et al. (2012) optimized the choice of greenhouse structure, cover material, shading and thermal screens, whitewash, heating and cooling system, CO_2 enrichment system for Spain and the Netherlands. Adopting the same modelling framework, Naseer et al. (2021) identified the optimal design for Norway among five predefined design alternatives.

Vanthoor et al. (2012) used the controlled random search method, which was originally developed for tackling continuous optimization problems (Price, 1977), to explore the solution space. However, the greenhouse design optimization problem is more suitable to be treated as a combinatorial optimization problem, as it involves discrete decisions regarding whether to include specific design element and which types to choose. In this regard, the genetic algorithm (GA) is an appropriate method (Holland, 1992). GAs fall under the category of evolutionary algorithms and are often used to generate solutions to search and optimization problems (Mendes et al., 2019). In agriculture, GAs have been applied to analyze problems such as farm management practices (Lehmann et al., 2013; Villalba et al., 2019), orchard replacement decisions (West, 2019), and food resource allocation problems (Notte et al., 2016).

A second component of optimal greenhouse design is the choice of criteria for evaluating the performance of different systems. Some scholars used biological or physical performance criteria, such as production levels (Luo et al., 2005a) and the ability to maintain the indoor environment (Wang et. al., 2014). Economic indicators are also well-accepted criteria for selecting the optimal greenhouse design (e.g., Vanthoor et al., 2012; Naseer et al., 2021). Apart from economic performance, environmental impact of greenhouse production is also an increasing concern for stakeholders, especially policy makers. Modern greenhouse production is associated with a high level of greenhouse gas (GHG) emissions due to the intensive use of energy. Different greenhouse designs have varying energy requirements, resulting in different environmental impacts (Zhou et al., 2021). Different stakeholders may assign different weights on the economic and environmental performance, and a greenhouse design that is ideal for investors may not be preferred by policy makers. The economic and environmental performance of different greenhouse designs have been compared in some studies (e.g., Naseer et al., 2022b; Meyer-Aurich et al., 2012), but separately. However, for multi-stakeholder decision-making, the economic and environmental performance should be jointly assessed to achieve a form of consensus that reflects a trade-off between conflicting objectives and stakeholder priorities.

This study aims to identify greenhouse designs that are optimally adapted to the climate and market conditions for four different locations in China. The design elements considered are greenhouse structure, cover material, shading and thermal screens, heating and cooling systems, artificial lighting, CO_2 enrichment systems, and whitewash. In order to reduce the computational effort, a genetic algorithm was employed to explore the large solution space. To identify the designs that best fit stakeholders' preferences, a directional distance function approach was used to evaluate the overall performance of greenhouse designs in terms of economic and environmental performance. The optimal greenhouse designs were selected based on their ability to consistently deliver robust performance across different price scenarios. The resulting greenhouse designs were those where no improvement in economic performance can be achieved without compromising the environmental performance, and vice versa.

The remainder of this paper is organized as follows: Section 2 presents the combination of methods used in this paper, i.e., the bio-physical model for simulating greenhouse yield and energy use, the genetic search algorithm, and the directional distance function. This is followed by the description of the results in Section 3. The paper ends with Discussion and Conclusions.

3.2 **Materials and Methods**

Figure 3.1 presents the schematic overview of the combination of methods used in the greenhouse design optimization problem. A bio-economic model was used to evaluate the economic and environmental performance of a given greenhouse design (Min et al., 2022). A genetic algorithm was used to explore the large combinational solution space, using economic performance as the fitness function. The search of genetic algorithm produced a subset of promising greenhouse designs, the overall performance of which were then evaluated by a directional distance function which aims at improving the economic performance and reducing environmental impacts simultaneously. The categorical regression was used to estimate the impact of individual design element alternatives on economic and environmental performance.

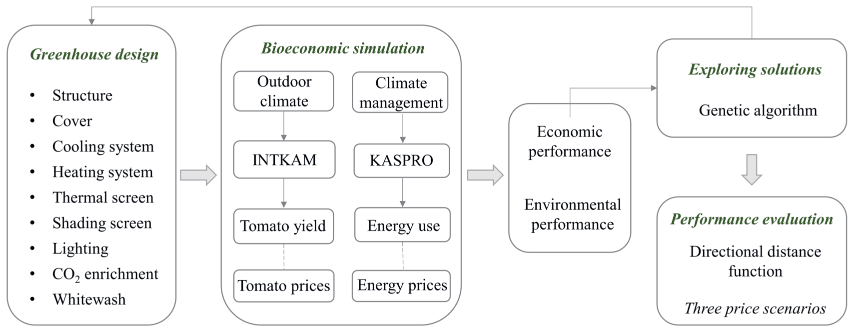

Figure 3.1. Schematic overview of the greenhouse design optimization problem.

This study focuses on nine greenhouse design elements: 1) type of structure, 2) cover material, 3) presence, type, and capacity of cooling system, 4) capacity of heating system, 5) presence and type of thermal screen, 6) presence and type of shading screen, 7) presence, type, and intensity of artificial lighting system, 8) presence and capacity of CO_2 enrichment system, and 9) presence of whitewash. An overview of the alternatives of each design element is given in Table 3.1

Table 3.1. Design element alternatives and associated economic parameters, encodings used for genetic algorithm.

Design elements choices	Investment	Investment	Lifetime	Maintenance
	¥ m^{-2}	¥ $unit^{-1}$	year	% $year^{-1}$
Structure (i = 1)				
A: Multi-tunnel, 1 vent 10 m^{-2}	156.3 [g]	-	15 [a]	2% [a]
B: Multi- tunnel, 1 vent 20 m^{-2}	143.3 [g]	-	15 [a]	2% [a]
C: Multi- tunnel, 1 vent 30 m^{-2}	131.0 [g]	-	15 [a]	2% [a]
D: Venlo, 1 vent 10 m^{-2}	241.7 [g]	-	15 [a]	0.5% [a]
E: Venlo, 1 vent 20 m^{-2}	218.3 [g]	-	15 [a]	0.5% [a]
F: Venlo, 1 vent 30 m^{-2}	208.3 [g]	-	15 [a]	0.5% [a]
Cover (i = 2)				
A: PE (polyethylene) film	7.8 [g]	-	7 [a]	5% [a]
B: Double PE film	15.7 [g]	-	7 [a]	5% [a]
C: Glass	55.0 [g]	-	15 [a]	0.5% [a]
Cooling systems (i = 3)				

A: No				
B: Fogging: 200 g h^{-1} m^{-2}	25.6 [c]	-	10 [a]	5% [a]
C: Fogging: 300 g h^{-1} m^{-2}	29.1 [e]	-	10 [a]	5% [a]
D: Fogging: 400 g h^{-1} m^{-2}	46.5 [e]	-	10 [a]	5% [a]
E: Pad and fan: 60 m^3 h^{-1} m^{-2}	22.2 [e]	-	10 [a]	5% [a]
F: Pad and fan: 90 m^3 h^{-1} m^{-2}	27.5 [e]	-	10 [a]	5% [a]
G: Pad and fan: 120 m^3 h^{-1} m^{-2}	31.0 [c]	-	10 [a]	5% [a]
Heating system (i = 4)				
A: Boiler: 1.16 MW ha^{-1}	-	412,920 [e]	15 [a]	1% [a]
B: Boiler: 1.74 MW ha^{-1}	-	432,000 [e]	15 [a]	1% [a]
C: Boiler: 2.32 MW ha^{-1}	-	475,200 [e]	15 [a]	1% [a]
Thermal screen (i = 5)				
A: No				
B: a transparent woven screen with transmission of 72%	12 [b]	-	5 [a]	5% [a]
C: made of non-transparent bands woven with black and transparent threads. Both side of screens are white	18 [b]	-	5 [a]	5% [a]
D: a light blocking screen, white on one side and black on the other side	27.5 [b]	-	5 [a]	5% [a]
E: Double-layer, the top layer an aluminized screen, and the low layer a woven black screen	32.2 [e]	-	5 [a]	5% [a]
Structure for thermal screen	42 [b]	-	10 [e]	5% [e]
Shading screen (i = 6)				
A: No				
B: shading factor 36%	13.5 [b]	-	5 [a]	5% [a]
C: shading factor 45%	11 [b]	-	5 [a]	5% [a]
D: shading factor 56%	12 [b]	-	5 [a]	5% [a]
Structure for shading screen	42 [b]	-	10 [e]	5% [e]
Lighting (i = 7)				

A: No supplemental lighting				
HPS (High-pressure sodium) bulbs (2.3 μmol J^{-1})		0.2 [a] ¥ W^{-1}	10,000 [a] hr	1% [a]
B: 50 μmol m^{-2} s^{-1}				
C: 100 μmol m^{-2} s^{-1}				
D: 150 μmol m^{-2} s^{-1}				
E: 200 μmol m^{-2} s^{-1}				
LED (light-emitting diode) lamp (3.1 μmol J^{-1}),	see Appendix 3A	4.2 [f] ¥ W^{-1}	35,000 [a] hr	0.5% [a]
F: 50 μmol m^{-2} s^{-1}				
G: 100 μmol m^{-2} s^{-1}				
H: 150 μmol m^{-2} s^{-1}				
I: 200 μmol m^{-2} s^{-1}				
HPS fixtures		0.9 [a] ¥ W^{-1}	7 [a]	1% [a]
Cabling		0.9 [a] ¥ W^{-1}	10 [a]	1% [a]
CO_2 enrichment (i = 8)				
A: no				
B: 50 kg CO_2 ha^{-1} h^{-1}				
C: 100 kg CO_2 ha^{-1} h^{-1}				
D: 150 kg CO_2 ha^{-1} h^{-1}				
E: 200 kg CO_2 ha^{-1} h^{-1}				
Pure CO_2 kg^{-1}	-	1 [d]	-	-
CO_2 distribution system	3.7 [c]	-	10 [a]	5% [a]
Whitewash (i = 9)				
A: No				
B: 50% transmission	0.7 [e]	-	1	0

Note: The cost of the “Structure for thermal screen” is incurred only when thermal screen is incorporated. This rule also applies to the “Structure for shading screen”, “HPS fixtures”, “Cabling”, and “CO_2 distribution system”.

a. Raaphorst et al. (2019)
b. Greenhouse screen consultant (Y. Ying, personal communication, June 7, 2022)
c. Construction budget of a tomato glasshouse in Shanghai, China.
d. Greenhouse grower (Y. Xie, personal communication, July 19, 2022)
e. Vanthoor et al. (2012)
f. Supplemental lighting consultant (X. Chen, personal communication, Nov 26, 2022)

g. Average costs provided by three greenhouse construction companies in China.

3.2.1 Bio-physical simulation of different greenhouse designs

This study uses a biophysical model INKTAM-KASPRO to simulate yield and energy use under different greenhouse designs. KASPRO is a dynamic greenhouse climate model that computes the greenhouse climate as a function of outdoor climate conditions and greenhouse climate management settings (De Zwart, 1996). The greenhouse climate computed by KASPRO is then fed into the tomato crop simulation model INTKAM to compute the daily gross photosynthesis and ultimately fruit weight (Marcelis et al., 2008). The inputs of the INKTAM-KASPRO are the greenhouse design configuration, outdoor climate, and the indoor climate management strategies. The outputs of the INKTAM-KASPRO are the monthly tomato yield, natural gas use, electricity use, and CO_2 use. The outputs of the biophysical model provided inputs for the evaluation of economic and environmental performance of a greenhouse design.

Four locations were considered: Jinshan (East China), Langfang (North China), Weifang (East China), and Pingliang (Northwest China). The outdoor climate differs significantly across regions, and this could impact the optimal cropping and heating schedules. Furthermore, variations in the climate from year to year can have a significant impact on the economic and environmental performances of a greenhouse (Vanthoor et al., 2012). However, it is computationally infeasible to run the simulation with climate data from every historical year. Therefore, the solution adopted was to use the long-term climate data with sufficient meteorological representativeness for a location. To achieve this, we constructed a typical meteorological year climate dataset for each location using the historical climate data from 2000 to 2020 obtained from the ERA5 climate dataset (Hersbach et al., 2018), following the method used by Song et.al (2007). The details of construction of the typical year climate dataset are presented in Appendix 3B. Table 3.2 displays the climate characteristics of each region based on the constructed typical meteorological year climate dataset.

Table 3.1. Climate characteristics, cropping and heating schedules of four regions.

	Jinshan	Langfang	Weifang	Pingliang
Longitude	30°49'51.96" N	39°30'34.99" N	36° 42' 24.39" N	35°32'21.01" N
Latitude	121°20'38.40" E	116°41'40.99" E	119° 9' 42.33" E	106°41'10.0" E
Yearly gross radiation (MJ m^{-2})	5406.3	5764.3	5715.7	5593.3
Gross radiation in Dec, Jan, Feb (MJ m^{-2})	913.8	932	931.3	993.4
Average temperature in Jan (°C)	6.5	-3.7	-1.6	-2.7
Average temperature in Jul (°C)	28.7	27.5	27.4	22.9
Average humidity in Jul (%)	82.8	70.8	74.1	62.6
Transplanting date	Oct 1	Sep 15	Sep 15	Jan 1
Heating start date	Dec 1	Oct 25	Nov 5	Oct 10
Heating end date	Apr 20, next year	Apr 13, next year	Apr 20, next year	Apr 30
Final harvest date	Jul 1, next year	Jul 10, next year	Jul 10, next year	Dec 15
Weeks of production	39	43	43	50

For the greenhouse climate manage strategies, we obtained the temperature and screen use setpoints from two Chinese growers and a greenhouse consultant (K. Yang, personal communication, December 5, 2019; Y. Xie, personal communication, February 6, 2022; Y. Ying, personal communication, June 7, 2022). The CO_2 setpoint, which refers to the desired indoor CO_2 concentration, increases with the use of lights and deceases with the opening of vent. In practice, the growers adjust their climate management strategies daily in response to weather conditions. The dependencies between the climate setpoints and the weather conditions were captured by the proportional band parameter (Pband). The detailed greenhouse climate management strategy can be found in Appendix 3C. The same climate setpoints were applied across all four locations to ensure that any differences in design performance were solely attributed to local climate and market conditions.

3.2.2 Economic Performance evaluation

The economic performance of a greenhouse design is defined as the annual operating income from greenhouse production:

$$\Pi = -EAC_{sum} + R - C_{var} \tag{3.1}$$

where Π (¥ m^{-2} year^{-1}) is the annual operating income from greenhouse production, R (¥ m^{-2} year^{-1}) is the annual revenue generated from harvested tomatoes, EAC_{sum} (¥ m^{-2} year^{-1}) is the annual fixed costs incurred from the depreciation and maintenance of greenhouse structure and equipment. C_{var} (¥ m^{-2} year^{-1}) is the variable costs of production.

Greenhouse structure and equipment have different life spans, and equipment replacement occurs at different times. To compare the fixed costs of different design elements with unequal lifetimes, the fixed costs associated with each design element was expressed as the Equivalent Annuity Cost (EAC). The total fixed costs of owning and maintaining the greenhouse is the sum of the EAC of each design element.

$$EAC_i^j = \frac{I_i^j \cdot r}{1 - (1 + r)^{-n_i^j}} + I_i^j \cdot m_i^j \tag{3.2}$$

$$EAC_{sum} = \sum_{i=0}^{9} EAC_i^j \tag{3.3}$$

where EAC_i^j is the Equivalent Annuity Cost of design element i with alternative j. I_i^j (¥ m^{-2}) is the initial investment cost of design element i with alternative j. n_i^j is the lifetime of design element i with alternative j in years. r is the discount rate, calculated with the Weighted Average Cost of Capital method (see Appendix 3D). m_i^j (% year^{-1}) is a fixed percentage of the initial investment costs, reflecting the annual maintenance costs of design element i with alternative j. An overview of the initial investment costs and maintenance costs of the nine design elements can be found in Table 3.1.

The annual revenue R is the sum of the economic value of tomatoes produced in all months:

$$R = \sum_{t=1}^{12} P_{tomato}^t * Q_{tomato}^t \tag{3.4}$$

where P_{tomato}^{t} (¥ kg^{-1}) is the tomato price of month t. Q_{tomato}^{t} (kg m^{-2}) is the harvested tomato of month t.

Variable costs C_{var} is the sum of natural gas costs, electricity costs, CO_2 costs (if any), and other costs such as seedlings, material, fertilizer, crop protection, labour costs. The costs of natural gas was modelled on a monthly basis. C_{var} is given by:

$$C_{var} = \sum_{t=1}^{12} P_{gas}^{t} * Q_{gas}^{t} + P_{elec} * Q_{elec} + P_{CO_2} * Q_{CO_2} + C_{other} \quad (3.5)$$

where P_{gas}^{t} (¥ m^{-3}) is the natural gas price of month t. Q_{gas}^{t} (m^3 m^{-2}) is the natural gas use per unit area of month t. Annual heating costs is the sum of the product of P_{gas}^{t} and Q_{gas}^{t} of all months. We used the average monthly price of liquid natural gas from 2017 to 2022, the longest period for which data are available, to represent the long-term natural gas price (Table E2, Appendix 3E).

Unlike liquid natural gas, the price of electricity in China is set by the government and has little variation from month to month. Therefore, a constant electricity price P_{elec} (¥ kWh^{-1}) was applied. The electricity price is 0.682 ¥ kWh^{-1} for Jinshan, 0.512 ¥ kWh^{-1} for Langfang, 0.525 ¥ kWh^{-1} for Weifang, and 0.439 ¥ kWh^{-1} for Pingliang. Q_{elec} (kWh m^{-2} year^{-1}) is the electricity use for lighting and empowering other machineries.

Q_{CO_2} is the amount of pure CO_2 (kg m^{-2} year^{-1}) supplied. P_{CO_2} (¥ kg^{-1}) is the price of pure CO_2, which remains constant with no monthly variation. Labour use was divided into non-harvest labour and harvest labour, the latter was dependent on tomato yield. Variable costs not related to energy and labour use were assumed to be the same for all locations.

Monthly wholesale prices for cherry tomatoes in 2021 for each region were aggregated by taking the average price of several markets within the same region (Table E1, Appendix 3E). These price data do not differentiate between variety and quality differences between field-grown and greenhouse tomatoes. Greenhouse-grown tomatoes are marketed as premium agricultural products and can command higher prices due to their superior quality and brand recognition (Wang, 2020; Zhang, 2010). A price premium of 50% was added to the wholesale price to represent the prices of tomatoes produced in modern greenhouses.

3.2.3 Environmental performance evaluation

The environmental performance of a greenhouse design is a multidimensional construct that encompasses many aspects, such as the release of hazardous chemicals into water systems, water use efficiency, soil degradation, and GHG emissions to the atmosphere (Zhou et al., 2021). Assuming soilless cultivation and the same irrigation system for each greenhouse design, variations in the environmental performance of each design primarily stem from differences in GHG emissions from energy consumption (Torrellas et al. 2012). Therefore, to assess the environmental performance of greenhouse designs, GHG emissions from energy use during the cultivation phase were taken into account. Emissions from greenhouses construction, product storage and transportation were not included[7]. The three main types of GHGs considered were carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), which have varying effects on global warming. Emissions of each type of GHG were converted into CO_2 equivalent emissions using specific global warming potentials (GWPs), as shown in Table 3.3. The environmental impact of a greenhouse design was computed using equation (3.6):

$$E = \sum_{GHG} \left(Q_{gas} * e_{gas} * GWP_{gas} \right) + Q_{elec} * e_{elec} \tag{3.6}$$

where E (kg m^{-2}) is the total amount of CO_2 equivalent emissions per unit area. Q_{gas} (m^3 m^{-2}) and Q_{elec} (kWh m^{-2}) are the annual consumption of natural gas and electricity per unit area. e_{gas} is the emission factor of natural gas (liquids) for the specified type of greenhouse gas. GWP_{gas} (CO_2e kg^{-1}) is the global warming potentials for the specified type of greenhouse gas. The emission factor of purchased electricity e_{elec} differs by region, depending on the proportion of electricity generated from renewable energy sources in the regional grid (Qu et al., 2017). Table 3.3 shows the emission factors of liquid natural gas and electricity.

[7] The GHG emission reporting guidelines for facility agriculture enterprises in China do not require reporting emissions from the construction and transportation phases. The guidelines specify the scope of the GHG assessment to include fossil fuel consumption, purchased electricity, and chemical use for greenhouse cultivation activities. Consequently, emissions related to other stages are of lesser concern to investors and policy makers in China.

Table 3.2. Emission factors for greenhouse gases emissions from energy use in greenhouse production.

Energy type	GHG type	Emission factor	Unit	GWP
Liquid natural gas	CO_2	64200 [a]	kg TJ^{-1}	1
	CH_4	10 [a]	kg TJ^{-1}	28 [b]
	NO_2	0.6 [a]	kg TJ^{-1}	265 [b]
Electricity	CO_2e	Langfang: 0.9236 [c]	kg kWh^{-1}	1
		Weifang: 0.8007 [c]		
		Jinshan: 0.6392 [c]		
		Pingliang: 0.5312 [c]		

a. Source: IPCC (2007), volume 2, Chapter 2, Table 2.5.

b. Source: IPCC (2014), Box 3.2, Table 1, with time horizon for 100 years.

c. Source: Qu et al. (2017).

Note: net calorific value of liquid natural gas: 51434 MJ ton^{-1}. Net calorific value of natural gas: 38.931 MJ m^{-3}. One ton of liquid natural gas was converted to 1320 m^3 of natural gas.

3.2.4 Search strategy – genetic algorithm

For the given set of design elements, the number of possible design alternatives would be equal to 340,200. A simulation for one design takes 20 seconds; hence, exploring all design alternatives would take 197 days, and this number is multiplied by four as we would like to explore the optimal design for four locations. Given this enormous computational time, it is impractical to simulate all design alternatives for each location. To ease the computational effort, a genetic algorithm (GA), an adaptive heuristic search algorithm based on Darwinian natural selection (Aytug et al., 2003, Mayer et al., 1999), was employed to search for close-to-optimal designs.

GA has five basic components: 1) a genetic representation of solutions (in this case, the representation of greenhouse designs) to the problem, 2) A way to generate an initial population of solutions, 3) an evaluation function to calculate the fitness score of solutions, 4) crossover and mutation operators to alter the genetic composition of off-springs during reproduction, and 5) Values for the parameters of GA (Zbigniew,1996). The steps of genetic algorithm are:

1. *Initialization*. Define N, the size of population. Randomly generate N design strings as the *initial population*.
2. Define the *initial population* as the *current population*.
3. Initialize $Counter = 0$.
4. Define the termination condition, the maximum number of iterations $Counter_{max}$.

While $Counter < Counter_{max}$:

5. *Evaluation*. Calculate the economic and environmental performances of each design in the *current population*.
6. *Selection*. Randomly draw two design strings from the current population, select the design string with the higher economic performance to enter the *parent pool* (binary tournament selection). Repeat this process until the size of *parent pool* reaches N.
7. *Crossover*. Each string in the *parent pool* has a probability of $P_{crossover}$ of being removed from the *parent pool* and selected to enter the *mating pool*. Randomly choose two strings from the *mating pool* as the parent chromosomes. Select two crossover points at random and swap the bits of parent chromosomes between the two points, resulting two offspring chromosomes. The offspring chromosomes and the remaining members of the *parent pool* together constitute the *population after crossover*.
8. *Mutation*. The mutation operator randomly changes any position of the string to a random different letter with a probability of P_{mutate}. After applying the mutation operator for each design string in the *population after crossover*, we obtain the *population after mutation*.
9. Update the *population after mutation* as the *current population*. Update the string with the highest economic performance as the *best string.*
10. Iteratively execute steps 5 to 9 until meeting the stopping criteria ($Counter = Counter_{max}$).

A key step of GAs is to encode a solution of a real-world problem into a chromosome. GA was originally encoded as binary strings, however in the real world, especially the field of engineering, many problems cannot be represented with binary encoding (Gen & Cheng, 1999). This holds true for the greenhouse design optimization problem, as each design component consists of more than two design options. Therefore, we used literal permutation encoding to represent a greenhouse design as a string of nine letters, where each letter represents a design element and its corresponding option. The index of the design component and the letter representation of the options are given in Table 3.1. One example of a design string is *DCBABAABA*, which represents a Venlo-glasshouse with one vent per 10 m^2 floor area, a fogging system with the capacity of 200 g h^{-1} m^{-2}, a boiler with heating capacity of 1.16 MW ha^{-1}, transparent thermal screens (transmissivity 72%), no shading screen, HPS lamps with light intensity of 50 μmol m^{-2} s^{-1}, CO_2 enrichment system at a dosing rate of 50 kg CO_2 ha^{-1} h^{-1}, no whitewash applied. Glass cover is infeasible for multi-tunnel structure, and PE film cover are considered for Venlo-type structure. Thus the strings with $i_1 = \{A, B, C\}$ and $i_2 = C$, or $i_1 = \{D, E, F\}$ and $i_2 = \{A, B\}$ are infeasible solutions and should be removed from the solution space. During the iterations of GA, the infeasible design strings were always converted to feasible ones.

The choice of population size, crossover and mutation probabilities is critical to the efficiency of GA. A small population size could lead the algorithm to provide poor solutions, while a too large population size would require more computation time to find a good solution (Diaz-Gomez & Hougen, 2007). In general, the suitable population size should be proportional to the number of dimensions of the problem (Harik & Lobo, 1999). A good balance between the crossover and mutation probabilities could direct the search towards promising regions, while maintaining the degree of diversity in the population, to avoid premature convergence (Harik & Lobo, 1999). Usually, the values for these parameters are chosen empirically for the specific class of optimization problems (Eremeev, 1999). After experimenting with a number of parameter combinations, we chose $N = 400, P_{crossover} = 0.5, P_{mutate=}0.1, Counter_{max} = 60$.

3.2.5 Overall performance evaluation - the directional distance function approach

We used the directional distance function approach to evaluate the overall performance of greenhouse production systems in terms of the revenues and GHG emissions generated. Following Chung et al. (1997), under the hypothesis of variable rate of return to scale, the directional distance function is defined as $\vec{D}(EAC_{sum}, C_{var}, \mathrm{R}, \mathrm{E}; \vec{d})$, The two types of inputs are EAC_{sum} and C_{var}. The two types of outputs are the (desired) annual revenue and the (undesired) GHG emissions of production. $\vec{d}$ is the directional vector, defined as $\vec{d} = (w^{R}_{stakeholder} * \mathrm{R}_0, -w^{GHG}_{stakeholder} * E_0)$, where $w^{R}_{stakeholder}$, $w^{GHG}_{stakeholder}$ represent the relative importance (weights) of revenue increase and environmental impacts reduction in the view of the stakeholders (investors or policy makers). This choice of directional vector implies that for given levels of inputs, the stakeholder aims at simultaneously increasing revenue at the rate of $w^{R}_{stakeholder}$, and decreasing GHG emissions at the rate of $w^{GHG}_{stakeholder}$. The values for w^R and w^{GHG} are 0.86 and 0.14 for investors, and 0.7 and 0.3 for policy makers. These values are the averaged relative importance of economic and environmental performance according to ten greenhouse investors and policy makers. The values were obtained through a survey with the stakeholders and calculated by using the Best-Worst method (Unpublished results of Min et al., see Appendix 3F).

Assuming that $k = 1, \dots, K$ is the index of greenhouse design. The performance of a greenhouse design is evaluated by the measure of inefficiency β. The inefficiency of greenhouse design k' can be calculated as solutions to the following linear programming problems:

$$\max_{\beta,\lambda} \beta \tag{3.7}$$

s.t.

$$\sum_{k=1}^{K} \lambda_k EAC_{sum\_k} \leq EAC_{sum\_k'} \tag{3.8}$$

$$\sum_{k=1}^{K} \lambda_k C_{var_k} \leq C_{var_{k'}} \tag{3.9}$$

$$\sum_{k=1}^{K} \lambda_k \mathrm{R}_k \geq (1 + \beta w^{R}_{stakeholder}) \mathrm{R}_{k'} \tag{3.10}$$

$$\sum_{k=1}^{K} \lambda_k \mathrm{GHG}_k \geq (1 - \beta w^{GHG}_{stakeholder}) GHG_{k'} \tag{3.11}$$

$$\sum_{k=1}^{K} \lambda_k = 1 \tag{3.12}$$

$$\lambda_k \geq 0, \beta \geq 0 \tag{3.13}$$

A greenhouse design is considered to be fully efficient when β takes the value zero.

3.2.6 Scenario analysis – find out robust greenhouse designs

The profitability of greenhouse production faces uncertainty due to fluctuating input and output prices. A greenhouse system that is considered optimal based on a given set of prices may not remain optimal for other price scenarios. A good greenhouse design should possess resilience and deliver robust performance in a dynamic market environment. To find out greenhouse designs that are robust to different price settings, we conceived three price scenarios: the baseline scenario, the low tomato price scenario, and the high energy cost scenario. The baseline scenario used 2021 tomato and energy prices as inputs for the simulation. The low tomato price scenario assumed a 30% reduction in tomato prices compared to the baseline scenario. In the high energy cost scenario, both gas and electricity prices were assumed to be 20% higher than the 2021 levels.

For each price scenario, we calculated the inefficiency scores β for both investors (β_{invest}) and policy makers (β_{policy}), which produced an approximation of the efficiency frontier. Designs with $\beta_{invest} = \beta_{policy} = 0$ were considered efficient for that specific price scenario. Greenhouse designs that were found to be efficient across all three price scenarios were considered robust.

To explore the relationship between the design elements and annual operating income or GHG emissions (under the baseline scenario), we performed categorical regression analyses. The interaction terms between the level-specific lighting and CO_2 dosing choices were included, as CO_2 enrichment and supplemental lighting were found to have a synergistic effect in increasing the light use efficiency of crops (Heuvelink & Dorais, 2018). A positive coefficient indicates that, ceteris paribus, selecting the specific design element leads to a higher operating income than the baseline choice. Conversely, a negative coefficient indicates a lower operating income compared to the baseline choice.

3.3 Results

For each location, the genetic search examined between 11,195 and 18,616 greenhouse designs, which represented 3.3% to 5.5% of all possible designs. Section 3.3.1 and 3.3.2 present the top five efficient designs based on economic and environmental performance, respectively, for each location. Results of the categorical regression for the operating income and GHG emissions are reported in Section 3.3.3 and 3.3.4, respectively.

3.3.1 Efficient greenhouse designs with the highest operating income

Table 3.4 presents the five efficient designs with the highest operating income in the baseline scenario for each location. The differences in profit per m^2 between the five designs are small, but with an average-sized greenhouse size of 1.5 ha, the cumulative difference can be large.

For Jinshan, a Venlo-type structure with glass cover was found to be the most favorable choice. A small-capacity boiler (1.16 MW ha^{-1}) and thermal screen with moderate energy-saving but high transmissivity was always selected. No cooling system or shading screen was chosen among the three efficient designs with the highest operating income in the baseline scenario. LED lamps with a high light intensity (200 μmol m^{-2} s^{-1}) coupled with CO_2 dosing at rate above 100 kg ha^{-1} h^{-1} were selected. Whitewash was selected only once out of the five efficient designs.

For Langfang, the recommended structure and cover were either a multi-tunnel structure with single PE film or a Venlo-type structure with glass cover. Given the cold winters in Langfang, it was suggested to opt for a high-capacity boiler (2.23 MW ha^{-1}) along with double-layer thermal screens. All efficient designs had LED lamps with high light intensity and the maximum CO_2 dosing rate, as well as whitewash.

For Weifang, a multi-tunnel structure and shading screens with a shading level of 36% were selected in three out of the five listed designs. When using single PE film as the cover material, which has higher transmissivity than double PE film, the transparent thermal screens were recommended. This choice of cover material and thermal screen aimed to increase light use efficiency and maximize yield. On the other hand, when double PE film, which has better insulation but less transmissivity than single PE film, was selected, the recommended design consisted of a small-capacity boiler and double-layer thermal screen with excellent insulation but no transmissivity, with the focus on maximizing energy savings and reducing variable costs.

Similar cover and thermal screen combinations were recommended for Pingliang, with glass or single PE film coupled with transparent thermal screens, and double PE film coupled with double-layer screens. For Weifang, LED lamps with high light intensity were selected, together with CO_2 dosing rate at 200 kg ha^{-1} h^{-1}. No whitewash was applied in the listed designs.

For Pingliang, the efficient design with the highest operating income in the baseline scenario was a relatively low-cost multi-tunnel structure with single PE film, without cooling system, shading screen or whitewash. LED lamps with the highest light intensity and a CO_2 enrichment system at the highest dosing rate were always present among the five listed designs.

Table 3.3. Simulation results per m^2 of the efficient greenhouse designs with the highest operating income for each location.

Design element choice									Simulation outcome				
ST	**CV**	**FG**	**HT**	**TS**	**SS**	**LT**	**CO_2**	**WW**	EAC	R	C_{var}	Π	GHG
Jinshan													
Venlo	Glass	No	1.16	Transp	No	LED 200	200	No	81	543	243	223	118
Venlo	Glass	No	1.16	Transp	No	LED 200	200	Yes	83	546	247	220	121
Venlo	Glass	No	1.16	Transp	No	LED 200	100	No	81	529	235	217	118
Venlo	Glass	200	1.16	Transp	36%	LED 200	200	No	99	540	234	211	114
Venlo	Glass	300	1.16	Transp	36%	LED 200	150	No	98	533	231	209	115
Langfang													
MT	S-PE	No	2.23	D-layer	36%	LED 200	200	Yes	91	751	256	405	184
MT	S-PE	300	2.23	Transp	No	LED 200	200	Yes	77	745	264	405	176
Venlo	Glass	200	2.23	D-layer	36%	LED 200	200	Yes	107	760	252	403	182
Venlo	Glass	300	2.23	D-layer	36%	LED 200	200	Yes	107	761	252	403	182
MT	S-PE	200	2.23	D-layer	No	LED 200	200	Yes	84	753	267	403	182
Weifang													
MT	D-PE	No	1.16	D-layer	36%	LED 200	200	No	92	502	243	168	161
MT	S-PE	No	2.23	Transp	36%	LED 200	200	No	81	495	248	167	146

MT	S-PE	No	1.74	Transp	36%	LED 200	200	No	80	495	348	167	147
Venlo	Glass	200	2.23	Transp	No	LED 200	200	No	84	502	251	167	146
Venlo	Glass	300	2.23	Transp	No	LED 200	200	No	85	502	251	166	146
Pingliang													
MT	S-PE	No	1.16	Transp	No	LED 200	200	No	72	795	214	511	115
Venlo	Glass	200	2.23	Transp	36%	LED 200	200	No	100	814	208	507	112
Venlo	Glass	No	1.16	Transp	36%	LED 200	200	No	94	807	206	507	112
Venlo	Glass	300	2.23	Transp	36%	LED 200	200	No	100	814	208	507	112
MT	D-PE	200	1.74	D-layer	36%	LED 200	200	No	100	816	211	506	123

ST stands for structure, *MT* stands for multi-tunnel, *CV* stands for cover, *FG* stands for fogging, *HT* stands for heating capacity, *TS* stands for thermal screen, *SS* stands for shading screen, *LT* stands for lighting, CO_2 stands for CO_2 enrichment, *WW* stands for whitewash. *S-PE* stands for Single PE. *D-PE* stands for Double PE. *Transp* stands for Transparent. *D-layer* stands for Double layer.

3.3.2 Efficient greenhouse designs with the lowest greenhouse gas emissions

Table 3.5 displays the top five efficient designs with the lowest GHG for each location, under the condition of a positive operating income in all three price scenarios. None of the designs with the best environmental performance for Langfang and Pingliang included supplemental lighting. However, LED lamps with an intensity of 200 μmol m^{-2} s^{-1} were necessary, in order to maintain positive operating income across all price scenarios for Jinshan and Weifang.

Unlike the five efficient designs in Table 3.4 for Langfang, which favored double-layer thermal screens, transparent thermal screens were selected when ranked on environmental performance. Conversely, most of the designs for Pingliang in Table 3.4 selected transparent thermal screens, but double-layer thermal screens became the preferred option when ranked on environmental performance. There are trade-offs between economic and environmental performance, and generally, GHG increase with operating income.

Table 3.4.Simulation results per m² of the efficient greenhouse designs with the lowest GHG for each location, under the condition of positive operating income in all price scenarios.

Design element choice									Simulation outcome				
ST	**CV**	**FG**	**HT**	**TS**	**SS**	**LT**	**CO_2**	**WW**	EAC	R	C_{var}	Π	GHG
Jinshan													
Venlo	Glass	300	1.16	Transp	36%	LED 200	200	No	99	540	234	211	114.4
Venlo	Glass	300	1.16	Transp	36%	LED 200	150	No	99	533	231	208	114.4
Venlo	Glass	No	1.16	Transp	36%	LED 200	100	No	93	521	227	206	114.4
Venlo	Glass	200	1.16	Transp	36%	LED 200	150	No	98	533	231	209	114.5
Venlo	Glass	400	1.74	Transp	36%	LED 200	200	No	102	541	235	208	114.9
Langfang													
MT	D-PE	200	1.16	Transp	No	No	No	No	41	305	166	99	63.3
MT	D-PE	400	1.16	Transp	No	No	100	Yes	46	316	171	98	63.3
MT	D-PE	200	1.16	Transp	No	No	200	Yes	42	319	174	102	63.4
MT	S-PE	No	1.74	Transp	No	No	100	Yes	36	322	184	103	69.5
MT	S-PE	No	1.74	Transp	No	No	150	Yes	36	323	185	102	69.6
Weifang													
Venlo	Glass	No	1.16	Transp	36%	LED 200	50	No	91	467	227	150	142.1
Venlo	Glass	300	1.16	Transp	36%	LED 200	100	No	96	481	233	153	142.4
Venlo	Glass	No	1.16	Transp	36%	LED 200	150	No	91	488	236	162	142.4
Venlo	Glass	300	1.16	Transp	36%	LED 200	150	No	96	490	237	157	142.5
Venlo	Glass	400	1.16	Transp	36%	LED 200	100	No	100	482	233	151	142.5
Pingliang													
MT	D-PE	300	1.74	D-layer	45%	No	No	No	58	292	117	117	41.2
MT	D-PE	No	2.23	D-layer	No	No	150	Yes	44	300	126	130	41.5
MT	D-PE	No	1.16	D-layer	No	No	150	Yes	43	295	126	125	41.5
MT	D-PE	200	1.16	D-layer	No	No	100	No	47	301	125	129	41.6
MT	D-PE	300	1.16	D-layer	No	No	200	No	48	302	128	127	41.6

ST stands for structure, *MT* stands for multi-tunnel, *CV* stands for cover, *FG* stands for fogging, *HT* stands for heating capacity, *TS* stands for thermal screen, *SS* stands for shading screen, *LT* stands for lighting, *CO_2* stands for CO_2 enrichment, *WW* stands for whitewash. *S-PE* stands for Single PE. *D-PE* stands for Double PE. *Transp* stands for Transparent. *D-layer* stands for Double layer.

3.3.3 Relationship between the design element choice and operating income

The results of the categorical regression analysis on operating income are shown in Table G1 in Appendix 3G. Almost all parameters were significant at the 0.05 critical level, as could be expected for this number of observations. The analysis indicates that the choices of lighting system, structure, thermal screen, and CO_2 dosing rate were the most influential factors on the operating income. In contrast, the choices of cover material, boiler capacity, shading screen, and whitewash had relatively small impacts on the operating income of a tomato greenhouse.

A structure with lower vent area was more favourable across all locations. Using double PE film as the cover material reduced the operating income in Jinshan and Langfang but increased it in Weifang and Pingliang. A pad and fan cooling system was not suitable for a tomato greenhouse, as indicated by the negative coefficients for each location. A fogging system was economically beneficial only for Langfang. A boiler with a capacity of 1.16 MW ha^{-1} was the preferred choice for Jinshan and Weifang, while a capacity above 1.74 MW ha^{-1} was preferable for Langfang and Pingliang. Overall, the choice of boiler capacity had limited impact on the operating income. All types of thermal screens, compared to no thermal screen, significantly increased the operating income of a tomato greenhouse. The transparent and double-layer thermal screens were the most effective measures for increasing operating income. The presence of shading screens slightly decreased the operating income of a tomato greenhouse in Jinshan, while shading screens with a 36% shading factor was the best choice for the other locations.

LED lamp with an intensity of 200 μmol m^{-2} s^{-1} was found to be the optimal lighting solution for all locations. LED lamp almost always outperformed HPS lamps given the same light intensity. The operating income in Jinshan, Langfang, and Weifang significantly decreased when the light intensity fell below 100 μmol m^{-2} s^{-1}. CO_2 enrichment without the presence of supplemental lighting was only profitable for Pingliang. The significance and magnitude of the interaction term coefficients between lighting and CO_2 dosing rate indicated a synergistic effect between lighting and CO_2 enrichment. However, the synergistic effect was negative for Pingliang when a low light intensity (below 100 μmol m^{-2} s^{-1}) was applied. The combination of a high light intensity (200 μmol m^{-2} s^{-1}) and a high CO_2 dosing rate (200 kg CO_2 ha^{-1} h^{-1}) showed the best ability to improve operating income.

3.3.4 Relationship between the design element choice and GHG

Table G2 in Appendix 3G presents the regression results regarding the effect of individual design elements on GHG emissions. The results indicates that lighting was the primary contributor to GHG emissions. Compared to HPS lamp, using LED lamp produces less GHG emissions. Additionally, incorporating thermal screens can effectively reduce GHG emissions, particularly when utilizing transparent or double-layer thermal screens. Furthermore, greenhouse with smaller vent areas were found to generate fewer GHG emissions. In particular, the Venlo-type structure was found to contribute less to GHG emissions compared to multi-tunnel structure with the same vent area. Although double PE film offers better heat insulation, using it as the cover material slightly increased GHG emissions. This may be attributed to the reduction in light penetration, which can lead to longer lighting hours. Lastly, fogging capacity, boiler capacity, shading screen, CO_2 enrichment, and whitewash were found to have little impact on GHG emissions.

3.4 Discussion

The optimization of greenhouse design is complex as it involves the large combinational solution space and the interrelations between design elements, outdoor climate, and crops. This study demonstrates how a novel combination of operational research methods together with bio-economic modelling can effectively address the challenge of greenhouse design optimization. By coupling a genetic algorithm with a bio-economic greenhouse model, the solution space was reduced to 3% to 5% of the entire design space. The use a directional distance function approach for performance evaluation allows us to identify a range of designs that are located on the efficiency frontier, rather than a single optimal solution.

This study extends existing work on greenhouse design optimization in several ways. Previously, Vanthoor et al. (2012) focused solely on optimizing greenhouse designs based on economic performance. Torrellas et al. (2012) and Naseer et al. (2022b) evaluated both economic and environmental aspects of various greenhouse designs separately, without considering the trade-offs between them. Our study contributes to this field by optimizing greenhouse designs from both aspects, taking into account multiple stakeholders' preference. This approach enables us to identify solutions that are acceptable to both investors and policy makers. Furthermore, the impact of price uncertainty is often overlooked in previous studies. While a greenhouse design may be considered optimal under a given set of prices and costs, it may not remain optimal under different price scenarios. To address this, we accounted for price uncertainty by selecting designs that were robust (i.e., optimal) under different price scenarios.

Our results clearly indicate that different regions require distinct greenhouse designs tailored to local climate and market conditions. Based on the findings of our study, Chinese policy makers can design region-specific subsidy policies to support technologies that are well-suited for individual regions, rather than subsidizing a broad range of technologies. For instance, the Venlo-type glasshouse was the most suitable structure for Jinshan. Double-layer thermal screens are advantageous in colder regions such as Langfang for energy-saving purposes. Moreover, LED lighting and CO_2 enrichment should be promoted as a bundled technology due to their synergistic effect on enhancing economic returns. Our findings can also help Chinese investors to make more informed investment decisions. Investors could flexibly select suitable designs based on their available budget or other relevant factors among the identified optimal greenhouse designs.

Our approach can be applied to many real-world problems, particularly those embedded in complex systems with interactions between factors, where establishing analytical relationships between decision variables and performance measures is difficult. These types of problems often have multiple (and often conflicting) objectives, and simulating such systems can be time-consuming. Previous efforts have combined DEA with GA to address challenges such as supplier selection (Shadkam & Bijari, 2017), agricultural production (Whittaker et al., 2009), resource allocation in hospitals (Lin et al., 2013), and aircraft spare parts allocation (Lee et al., 2008). However, none of these approaches considered the presence of multiple stakeholders, whose weights for different objectives may differ. Therefore, our approach represents an advancement in this research domain.

Some further issues can be studied in future research. Firstly, it should be noted that this study employed the same greenhouse climate setpoints across all price scenarios. In reality, the optimal climate setpoints may vary depending on the price levels, and greenhouse growers may adjust climate setpoints with changes in energy prices (Los et al., 2021). Therefore, a model that optimizes greenhouse design and climate management simultaneously is worth further exploration. A bilevel optimization formulation may be well-suited to this context.

Secondly, the study used typical meteorological year climate data as inputs for its analysis. The typical meteorological year climate data was constructed based on climate data from 2000 to 2020. This implies that greenhouse designs were optimized to adapt to past climate conditions. However, in the context of climate change, it is also possible to take a forward-looking perspective and optimize greenhouse designs based on projected climate conditions for the next 20 years.

Weather conditions can vary greatly from year to year, affecting yield, energy use, and operating income. Different greenhouse designs may respond differently to weather uncertainties. For instance, a greenhouse design with excellent heat insulation may not produce the best economic outcome in a typical climate year but could potentially yield better results during an extremely cold year. Therefore, instead of focusing on typical climate conditions, it may be valuable to consider the production risk arising from weather uncertainty and examine the distribution of the economic outcomes. In this case, a robust optimization approach could be suitable.

Thirdly, it is worth mentioning that the environmental performance assessment in this study focused solely on GHG emissions generated from energy use. However, it should be acknowledged that the GHG emissions generated from the construction phase of different greenhouse designs can vary greatly. To calculate the emissions related to greenhouse construction, we would need detailed data on the materials and quantities associated with the design alternatives listed in Table 1. Unfortunately, such detailed information was not available. For a fairer assessment of the optimal greenhouse design, it would be more appropriate to include the GHG emissions associated with greenhouse construction, provided that data is accessible.

3.5 Conclusions

This paper reports several greenhouse designs that were found to be efficient in terms of economic and environmental performance for both investors and policy makers across various price scenarios. The results underscore the importance of tailoring greenhouse designs to local climate and market conditions, with specific recommendations for different regions. For example, the Venlo-type structure with glass cover is the most favorable choice for Jinshan, while a multi-tunnel structure appeared to be a more suitable for Langfang and Pingliang. Applying whitewash during summer is generally discouraged, except for in Langfang. Incorporating double-layer thermal screens in colder regions such as Langfang can be economically beneficial. In other cases, transparent thermal screen is a preferred choice to increase light use efficiency and improve yield.

The choice of lighting system, structure, thermal screen, and CO_2 dosing rate were among the most influential factors on operating income. When comparing LED to HPS lamps, LED lighting performs better in terms of both economic and environmental performance. However, it is crucial to note that lighting is the primary contributor to GHG emissions. As a result, the optimal designs identified either opt for no lighting or incorporated LED lamps with an intensity above 100 μmol m^{-2} s^{-1}, combined with a high CO_2 dosing rate. Low intensity lighting negatively affects both economic and environmental performance. The use of thermal screens, on the other hand, can effectively reduce GHG emissions.

Supplementary materials

Python code for performance evaluation of greenhouse designs and the implementation of genetic algorithm are available as supplementary materials at https://github.com/Xinyuan-wur/greenhouse-design-optimization

Declaration of interest statement

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Appendix 3A. Lighting installation initial investment costs calculation

Table A1. Parameters for lighting installation initial investment costs calculation, depending on the lamp type and lighting intensity.

Item	Parameter	Unit	HPS	LED
Efficacy	η^{HPS}, η^{LED}	μmol J^{-1}	2.3	3.1
Lamp investment	I_{bulb}^{HPS}, I_{lamp}^{LED}	¥ W^{-1}	0.2 [a]	4.2 [b]
Lamp lifetime	n_{bulb}^{HPS}, n_{lamp}^{LED}	hours	10,000 [a]	35,000 [a]
Lamp maintenance	m_{lamp}^{HPS}, m_{lamp}^{LED}	%	1.0 [a]	0.5 [a]
Fixture investment	$I_{fixture}^{HPS}$	¥ W^{-1}	0.9 [a]	/
Fixture lifetime	$n_{fixture}^{HPS}$	years	7 [a]	/
Fixture maintenance	$m_{fixture}^{HPS}$	%	1.0	/
Cabling investment	I_{cable}	¥ W^{-1}	0.9 [a]	0.9 [a]
Cabling lifetime	n_{cable}	years	10 [a]	10 [a]
Cabling maintenance	m_{cable}	%	1.0 [a]	1.0 [a]
Initial investment costs per floor area				
50 μmol m^{-2} s^{-1}	I_{HPS}^{50}, I_{LED}^{50}	¥ m^{-2}	43.5	82.3
100 μmol m^{-2} s^{-1}	I_{HPS}^{100}, I_{LED}^{100}	¥ m^{-2}	87.0	164.5
150 μmol m^{-2} s^{-1}	I_{HPS}^{150}, I_{LED}^{150}	¥ m^{-2}	130.4	246.8
200 μmol m^{-2} s^{-1}	I_{HPS}^{200}, I_{LED}^{200}	¥ m^{-2}	173.9	329.9

a. Raaphorst et al. (2019)

b. X. Chen, personal communication, Nov 26, 2022

Lighting installation consists of several components (bulbs, fixture, cabling for HPS; lamp and cabling for LED). The total investment costs of lighting installation (¥ m^{-2}), given a desired lighting intensity x (μmol m^{-2} s^{-1}), was calculated as:

$I_{HPS}^{x} = \left(I_{bulb}^{HPS} + I_{fixture}^{HPS} + I_{cable}\right) * x/\eta^{HPS}$ for HPS lamps, and

$I_{LED}^{x} = \left(I_{lamp}^{LED} + I_{cable}\right) * x/\eta^{LED}$ for LED lamps

The initial investment costs of each component was convert into the equivalent annuity cost (EAC), which is dependent on the lifetime (year) of the component. To calculated the lifetime of lamps, we divided the annual lighting hours, which is an output of the INTKAM-KASPRO model, by the lifetime (hour) of HPS bulb or LED lamp. The total EAC of lighting installation was give as:

$EAC_{HPS}^{x} = EAC_{HPS-bulb}^{x} + EAC_{HPS-fixture}^{x} + EAC_{cable}^{x}$ for HPS lamps, and

$EAC_{LED}^{x} = EAC_{LED-Lamp}^{x} + EAC_{cable}^{x}$ for LED lamps.

Appendix 3B. Typical year climate data based on the ERA5 climate dataset from 2000 to 2020

To construct the typical year climate data based on the ERA5 dataset from 2000 to 2020, we followed the same method of typical year selection as in Song et.al (2007), for the construction of Chinese Standard Weather Data.

The typical year climate data of each month is constituted by selecting a year between 2000 and 2020 with the most meteorological representativeness of the month. Seven climate indicators contribute to the measure of meteorological representativeness. The indicators were assigned with different weights W_i according to their importance in meteorological representativeness, as shown in Table B1.

Table B1. Climate indicators and the corresponding weights for meteorological typical year selection.

Indicator	**Weight W_i**
Daily average temperature	2/16
Daily minimum temperature	1/16
Daily maximum temperature	1/16
Daily average sky temperature	1/16
Daily average relative humidity	2/16
Global radiation downwards	8/16
Daily average wind speed	1/16

The selecting process is described as below:

1. Calculate for each indicator the monthly mean values of each year from 2000 to 2020: $X_{i,m,y}$, where i denotes the climate indicator under consideration, m denotes the month indices and y denotes the year indices.
2. Calculate for each climate indicator i, the mean $\bar{X}_{i,m}$ and the standard deviation $S_{i,m}$ across multiple years.
3. Calculate for each indicator i , the normalized monthly mean value of each year: $\eta_{i,m,y} = (X_{i,m,y} - \bar{X}_{i,m})/S_{i,m}$.
4. Calculate for each month and each year, the weighted sum normalized absolute monthly mean of all climate indicators: $D_{m,y} = \sum_i W_i \cdot |\eta_{i,m,y}|$
5. Select for each month, the year with the smallest $\min_y D_{m,y}$.

6. Create the meteorological typical year data by appending the monthly climate data of the selected year, so for each month, the monthly data from the year with the smallest $D_{m,y}$ become the same month data of the meteorological typical year.

Table B2. Selected years for each monthly for constructing the meteorological typical year climate dataset.

Month	**Jinshan**	**Langfang**	**Weifang**	**Pingliang**
January	2007	2008	2018	2019
February	2003	2015	2011	2015
March	2009	2004	2013	2014
April	2000	2001	2004	2009
May	2012	2015	2015	2015
June	2008	2016	2015	2011
July	2012	2013	2005	2009
August	2003	2010	2017	2000
September	2001	2020	2015	2015
October	2013	2008	2019	2011
November	2014	2001	2016	2008
December	2020	2019	2006	2015

Appendix 3C. Greenhouse climate management strategy

Table C1. Description of the greenhouse climate management strategy.

Parameter	Values	Description
$Tair_{\_heat}$ (day/night)	17°C/14°C	The heat is turned on when the indoor temperature (Tair) is below 17°C during the day and 14°C during the night.
$Pband_{\_heat}$	2°C, 100 W m^{-2}, 400 W m^{-2}	When radiation (Iglob) is below 100 W m^{-2}, $Tair_{\_heat}$ is unaffected and above 400 W m^{-2} $Tair_{\_heat}$ increases by 2°C. Between 100 and 400 W m^{-2}, $Tair_{\_heat}$ increment is linearly interpolated.
$Tout_{\_ThScr}$	10°C if Iglob < 100 W m^{-2}; 0°C if Iglob < 290 W m^{-2}	Thermal screen may be used when the outside temperature (Tout) is below 10°C and radiation is above 100 W m^{-2}. When Tout goes below 0°C, the thermal screen will be kept deployed until the radiation is above 290 W m^{-2}.
$Iglob_{\_ShScr}$	600 W m^{-2}, 800 W m^{-2}	The shading screen will be half closed when the radiation exceeds 600 W m^{-2} and fully closed when the radiation exceeds 800 W m^{-2}.
$Tair_{\_vent}$	16°C/19°C	Vent is open when Tair is above 19°C during the day and 16°C during the night.
$Pband_{vent}$	18°C if Tout < 6 °C, 4°C if Tout > 20°C	$Pband_{vent}$ is a key parameter that controls how large the temperature excess has to be before the leeward vents are fully opened. The maximum opening of vents is 100%. When Tout is below 6°C, the p-band is 18°C; when Tout is above 20°C, the p-band is 4°C. The windward vents only open when the leeward vents are opened above 50%.
$Tair_{\_fan}$	2°C	Fans will run on the maximum capacity when the difference between Tair and $Tair_{\_vent}$ excesses 2°C. The air can be cooled down to 0.85 of the wet-bulb temperature. The outlet temperature is 1.5°C above the average greenhouse temperature.
$RH_{\_fog}$	75%	Fogging system starts working when the indoor relative humidity (RH) drops below 75%.
$Pband_{\_fog}$	5%	Fogging system works at the maximum capacity when RH drops to 70%. The working capacity of fogging

		system is proportionally controlled from 0 to the maximum value.
$Time_{\_light\_on}$	00:00	Lamps are turned on at 00:00 after five weeks of planting; the maximum lighting hour is 18 hours per day.
$Iglob_{\_light\_off}$	400 W m^{-2}	Lamps are turned off when radiation is above 400 W m^{-2}.
$CO2_{\_setpoint}$ (day/night)	800 ppm/400 ppm	Extra CO_2 is applied is the indoor CO_2 concentration is below 800 ppm during the day, and 400 ppm during the night.
$CO2_{\_light}$	1000 ppm	CO_2 setpoint set to 1000 ppm if lights are on.
$CO2_{\_vent}$	100%, 20%; 50%, 40%; 25%, 75%	when the (leeward) vents are opened till 20%, the maximum CO2 dosing capacity is kept at 100%. When vents are opened till 40%, the CO2 dosing capacity is reduced to half its maximum capacity. When vents are opened above 70%, the dosing capacity stays at 25% of the maximum capacity.

Appendix 3D. Calculation of weighted average cost of capital (WACC)

Table D1. Calculation of weighted average cost of capital

Cost of debt after tax shield (CD)	**Rate**	**Source**
Cost of debt (Rd)	5.5%	The People's Bank of China (2022), with the assumption of 20% floating rate on the 5-year Loan Prime Rate of 2022 (4.6%)
Marginal tax rate (T)	0.0%	Enterprise Income Tax Law of the People's Republic of China, article 27 (2007)
Cost of debt after tax shield	5.5%	
Cost of equity (CE)		
Risk free rate (rfr)	2.79%	China 10-year government bond yield (Ministry of Finance of the People's Republic of China, 2022)
Market risk premium of China (rm)	4.94%	(Damodaran, 2022a)
Beta for farming sector in China (β)	0.79	(Damodaran, 2022b)
Cost of equity	6.69%	Calculated
Capital structure	Ratio	
Debt (D)	50%	Authors' assumption
Equity (E)	50%	Authors' assumption
WACC	6.10%	Calculated

The discount rate r was calculated using the WACC method as follows:

$$r = WACC = \frac{D}{D+E} \cdot CD + \frac{E}{D+E} \cdot CE = \frac{D}{D+E} \cdot Rd \cdot (1-T) + \frac{E}{D+E} \cdot (rfr + \beta \cdot rm)$$

Appendix 3E. Tomato and natural gas prices

Table E1. Monthly cherry tomato wholesale prices (¥ kg^{-1}) for 2021 (with 50% price premium).

Month	Jinshan[8]	Langfang	Weifang	Pingliang[9]
Jan	12.00	15.23	10.86	12.81
Feb	11.18	14.60	12.99	12.23
Mar	9.62	16.91	12.66	14.36
Apr	11.03	15.93	11.12	13.46
May	13.55	14.43	9.05	12.08
Jun	11.63	12.78	6.75	10.56
Jul	11.81	11.58	8.58	9.45
Aug	12.84	11.43	9.12	9.32
Sep	14.19	11.79	9.93	9.65
Oct	15.09	12.35	11.60	10.16
Nov	17.82	17.18	12.84	14.6
Dec	18.71	17.96	13.68	15.32

Source: National commercial information platform of agricultural product (nc.mofcom.gov.cn).

Table E2. Average monthly price (¥ m−3) of natural gas from 2017 to 2022 for four regions.

Month	Jinshan	Langfang	Weifang	Pingliang
Jan	4.93	4.76	4.89	4.62
Feb	5.03	4.69	4.91	4.24
Mar	4.56	4.44	4.75	4.05
Apr	4.32	4.12	4.51	3.87
Oct	4.37	4.36	4.45	4.25
Nov	4.95	4.93	5.07	5.02
Dec	5.11	4.84	5.23	5.05

[8] Cherry tomato prices of Jiangsu province were used as proxies for Jinshan cherry tomato prices due to the lack of data

[9] There are no price records for cherry tomato for Pingliang. Therefore, we estimated cherry tomato prices based on the price difference (92%) for globe tomatoes between Langfang and Pingliang. A transportation tarif of 1.2 ¥ kg^{-1} was applied for Pingliang, after consulting a greenhouse manager in Pingliang.

Appendix 3F. Derivation of stakeholder weights

The values of stakeholders' weight for revenue increase $w^{R}_{stakeholder}$ and environmental impacts reduction $w^{GHG}_{stakeholder}$ used in this study were derived based on the unpublished results of Min et al. This appendix explains how the survey was conducted and how the weights were derived.

The survey aimed to elicit the relative importance of the six criteria, including *cost-benefit* and *environmental impacts* of greenhouse technologies, among multiple stakeholders in the Chinese greenhouse sector. The survey was designed according to the guidelines of the Best-Worst method, a multi-criteria decision-making method developed by Rezaei (2015) for addressing complex problems with multiple conflicting and subjective criteria. The survey was documented in Excel format.

We collected data from four groups of stakeholders: greenhouse growers, private investors, machinery and equipment suppliers, and agricultural policy makers in China. Ten respondents for each group were reached through snowball sampling. Specifically:

Investors were general managers or directors in a modern greenhouse company, located in Beijing, Shanghai, Shandong, Gansu, Jiangsu, Yunnan, and Guangdong provinces. The sample of growers and investors covers the stakeholders of major modern greenhouse companies in China.

Policy makers were recruited from the local ministry of agriculture, agricultural research institutes, extension centers, and quasi-commercialized state-owned enterprises. Policy makers were only included if they had participated in the design of local agricultural policy or had been involved in local greenhouse projects.

The surveys were conducted through a web conferencing platform and presented to the respondents through screen sharing. Each respondent was presented with an overview of all evaluation criteria. The respondents were first asked to identify which criteria they considered the most and least important when adopting (for investors) or promoting (for policy makers) digital or automation technology for greenhouse production. Respondents were then instructed to compare the remaining criteria to the selected most and least important criteria by assigning a number between 1 and 9. Throughout the survey interview, respondents were also asked to explain their choices.

A BWM solver was employed to calculate the optimal weights and the consistency ratio. In case of inconsistency, respondents were asked if they were willing to reconsider their judgement for the most inconsistent pair-wise comparison. Figure F1 presents an example of a survey response that we collected.

the most important criterion	Cost-benefit

the least important criterion	Trialablity

Please evaluate the relative importance of [Cost-benefit] to other criteria (choose from 1 to 9)

Cost-benefit	1	2	9	3	3	6
	Cost-benefit	Environmental	Trialablity	Observability	Complexity	Compatibility

Please evaluate the relative importance of other criteria to [Trialablity] (choose from 1 to 9)

	Cost-benefit	Environmental	Trialablity	Observability	Complexity	Compatibility
Trialablity	9	6	1	4	4	2

Your weights

Weights	Cost-benefit	Environmental	Trialablity	Observability	Complexity	Compatibility
	0.39	0.21	0.04	0.14	0.14	0.07

Consistency check

Consistency ratio	0.0417	Consistency check passed
Consistency threshold	0.3337	

Scale of importance (1-9)

1: **Equal** importance
2: Somewhat between Equal and Moderate
3: **Moderately** more important
4: Somewhat between Moderate and Strong
5: **Strongly** more important than
6: Somewhat between Strong and Very strong
7: **Very strongly** important than
8: Somewhat between Very strong and Absolute
9: **Absulutly** more important

Figure F1. Example of a survey response.

After deriving the optimal weights for each respondent, we calculated the weight for each stakeholder group by taking the arithmetic mean of the optimal weights for individual respondents within the stakeholder group. The values for $w^{R}_{stakeholder}$ and $w^{GHG}_{stakeholder}$ were then calculated as:

$$w^{R}_{stakeholder} = \frac{w^{cost-benefit}_{stakeholder}}{w^{cost-benefit}_{stakeholder} + w^{environmental}_{stakeholder}}$$

$$w^{GHG}_{stakeholder} = \frac{w^{environmental}_{stakeholder}}{w^{cost-benefit}_{stakeholder} + w^{environmental}_{stakeholder}}$$

Appendix 3G. Categorical regression results: the effect of individual design element on operating income and GHG emissions

Table G1. Categorical regression results: the relationship between design element choice and the annual operating income (baseline scenario).

Variable	Design element choice	Jinshan	Langfang	Weifang	Pingliang
Structure_A	*Multi- tunnel, 1 vent 10 m^{-2}*	*baseline choice*			
Structure_B	Multi- tunnel, 1 vent 20 m^{-2}	24.7 (*0.3*)	34.9 (*0.4*)	26.2 (*0.3*)	36.3 (*0.5*)
Structure_C	Multi- tunnel, 1 vent 30 m^{-2}	39.1 (*0.2*)	52.0 (*0.3*)	41.7 (*0.3*)	55.0 (*0.5*)
Structure_D	Venlo, 1 vent 10 m^{-2}	8.4 (*0.3*)	7.7 (*0.5*)	5.3 (*0.4*)	10.6 (*0.7*)
Structure_E	Venlo, 1 vent 20 m^{-2}	33.5 (*0.3*)	41.8 (*−0.4*)	33.6 (*0.4*)	44.5 (*0.6*)
Structure_F	Venlo, 1 vent 30 m^{-2}	46.2 (*0.3*)	55.2 (*0.4*)	46.1 (*0.3*)	59.8 (*0.6*)
Cover_A	*Single PE film*	*baseline choice*			
Cover_B	Double PE film	−3.5 (*0.2*)	−5.1 (*0.2*)	0.7 (*0.2*)	7.0 (*0.4*)
Cooling_A	*No cooling*	*baseline choice*			
Cooling_B	Fogging: 200 g h^{-1} m^{-2}	−6.5 (*0.2*)	5.1 (*0.3*)	−4.9 (*0.2*)	−4.4 (*0.4*)
Cooling_C	Fogging: 300 g h^{-1} m^{-2}	−7.0 (*0.2*)	5.6 (*0.3*)	−5.7 (*0.2*)	−5.4 (*0.4*)
Cooling_D	Fogging: 400 g h^{-1} m^{-2}	−10.1 (*0.2*)	2.3 (*0.3*)	−9.0 (*0.3*)	−8.4 (*0.4*)
Cooling_E	Pad and fan: 60 m^3 h^{-1} m^{-2}	−42.2 (*0.3*)	−17.4 (*0.4*)	−22.2 (*0.3*)	−53.5 (*0.7*)
Cooling_F	Pad and fan: 90 m^3 h^{-1} m^{-2}	−54.1 (*0.3*)	−25.0 (*0.4*)	−32.6 (*0.3*)	−65.1 (*0.7*)
Cooling_G	Pad and fan: 120 m^3 h^{-1} m^{-2}	−64.6 (*0.3*)	−33.4 (*0.4*)	−40.8 (*0.4*)	−75.1 (*0.7*)
Heating_A	*1.16 MW ha^{-1}*	*baseline choice*			
Heating_B	1.74 MW ha^{-1}	−0.4 (*0.2*)	0.6 (*0.2*)	−0.5 (*0.2*)	1.4 (*0.3*)
Heating_C	2.32 MW ha^{-1}	−0.1 (*0.2*)	1.0 (*0.2*)	0.1 (*0.2*)	1.4 (*0.3*)
Thermal_screen_A	*No thermal screens*	*baseline choice*			
Thermal_screen_B	Transparent, 72% transimission	40.5 (*0.3*)	59.0 (*0.4*)	53.8 (*0.3*)	73.0 (*0.6*)
Thermal_screen_C	Non-transparent, white	23.8 (*0.3*)	35.5 (*0.4*)	31.2 (*0.4*)	46.8 (*0.7*)

Thermal_screen_D	Light blocking, one side black	22.5 (*0.3*)	39.0 (0.4)	33.8 (*0.4*)	47.6 (*0.7*)
Thermal_screen_E	Double-layer, top layer aluminized	32.9 (*0.3*)	57.4 (0.4)	49.8 (*0.3*)	70.0 (*0.7*)
Shade_screen_A	*No shade screens*	*baseline choice*			
Shading_screen_B	36% shading	−4.4 (*0.2*)	3.4 (0.2)	0.5 (*0.2*)	1.0 (*0.4*)
Shading_screen_C	45% shading	−8.6 (*0.2*)	−4.0 (0.3)	−4.8 (*0.2*)	−4.5 (*0.4*)
Shading_screen_D	56% shading	−9.1 (*0.2*)	−3.6 (0.3)	−5.1 (*0.2*)	−4.4 (*0.4*)
Light_A	*No lighting*	*baseline choice*			
Light_B	HPS, 50 µmol m^{-2} s^{-1}	−25.4 (*1.1*)	−8.8 (2.1)	−79.2 (*2.1*)	57.7 (*4.4*)
Light_C	HPS, 100 µmol m^{-2} s^{-1}	−49.9 (*1.1*)	−8.7 (2.1)	−92.4 (*1.9*)	28.0 (*3.9*)
Light_D	HPS, 150 µmol m^{-2} s^{-1}	36.7 (*0.8*)	154.4 (1.4)	−3.9 (*1.3*)	229.4 (*2.1*)
Light_E	HPS, 200 µmol m^{-2} s^{-1}	57.6 (*0.6*)	186.1 (1.0)	17.1 (*1.1*)	252.3 (*1.3*)
Light_F	LED, 50 µmol m^{-2} s^{-1}	−13.9 (*1.0*)	−3.6 (1.9)	−74.1 (*1.7*)	42.1 (*3.9*)
Light_G	LED, 100 µmol m^{-2} s^{-1}	−27.8 (*1.0*)	−9.5 (2.0)	−82.8 (*1.6*)	28.8 (*3.3*)
Light_H	LED, 150 µmol m^{-2} s^{-1}	72.1 (*0.8*)	159.6 (1.9)	10.4 (*1.2*)	224.8 (*2.6*)
Light_I	LED, 200 µmol m^{-2} s^{-1}	97.3 (*0.5*)	200.2 (0.7)	33.2 (*0.6*)	253.1 (*1.3*)
CO_2_A	*No CO_2 enrichment*	*baseline choice*			
CO_2_B	50 kg CO_2 ha^{-1} h^{-1}	−16.8 (*1.0*)	−26.8 (1.9)	−85.7 (*1.4*)	15.2 (*3.4*)
CO_2_C	100 kg CO_2 ha^{-1} h^{-1}	−18.9 (*0.9*)	−27.1 (1.2)	−87.5 (*1.1*)	13.4 (*2.5*)
CO_2_D	150 kg CO_2 ha^{-1} h^{-1}	−18.6 (*0.9*)	−32.3 (1.0)	−89.7 (*0.9*)	7.7 (*1.7*)
CO_2_E	200 kg CO_2 ha^{-1} h^{-1}	−19.3 (*0.8*)	−33.5 (1.0)	−89.3 (*0.8*)	6.0 (*1.4*)
Whitewash_A	*No whitewash*	*baseline choice*			
Whitewash_B	50% transmission	−4.6 (*0.1*)	2.3 (0.2)	−5.6 (*0.2*)	−8.8 (*0.3*)
light_B*CO_2_B		14.3 (*1.7*)	29.7 (3.3)	83.3 (*2.8*)	−39.2 (*6.1*)
light_B*CO_2_C		13.1 (*1.6*)	23.4 (2.8)	82.1 (*2.5*)	−38.5 (*5.8*)
light_B*CO_2_D		11.2 (*1.6*)	30.9 (2.5)	82.0 (*2.4*)	−36.0 (*4.9*)
light_B*CO_2_E		7.7 (*1.5*)	28.9 (2.4)	82.4 (*2.4*)	−41.5 (*4.7*)

light_C*CO_2_B	16.9	27.7	86.9	−22.9
	(*1.8*)	(3.3)	(*2.8*)	(*6.1*)
light_C*CO_2_C	15.1	24.8	85.3	−22.5
	(*1.6*)	(2.7)	(*2.4*)	(*5.3*)
light_C*CO_2_D	10.9	27.8	86.3	−19.7
	(*1.6*)	(2.5)	(*2.2*)	(*4.6*)
light_C*CO_2_E	9.9	28.2	83.6	−22.8
	(*1.5*)	(2.4)	(*2.2*)	(*4.2*)
light_D*CO_2_B	23.7	42.5	91.9	17.5
	(*1.4*)	(2.6)	(*2.0*)	(*4.4*)
light_D*CO_2_C	26.3	42.2	95.8	35.4
	(*1.3*)	(2.0)	(*1.8*)	(*3.5*)
light_D*CO_2_D	25.5	52.8	100.1	52.9
	(*1.3*)	(*1.8*)	(*1.7*)	(*2.8*)
light_D*CO_2_E	24.9	55.9	98.4	62.1
	(*1.2*)	(*1.8*)	(*1.6*)	(*2.6*)
light_E*CO_2_B	25.9	58.9	99.6	25.0
	(*1.2*)	(*2.2*)	(*1.9*)	(*3.6*)
light_E*CO_2_C	33.2	75.3	108.7	52.1(
	(*1.0*)	(*1.6*)	(*1.6*)	*2.7*)
light_E*CO_2_D	35.3	87.8	112.2	75.6
	(*1.0*)	(*1.4*)	(*1.4*)	(*1.9*)
light_E*CO_2_E	37.1	94.5	113.3	87.1
	(*1.0*)	(*1.4*)	(*1.4*)	(*1.6*)
light_F*CO_2_B	14.8	28.1	84.7	−14.4
	(*1.7*)	(*3.1*)	(*2.5*)	(*5.9*)
light_F*CO_2_C	13.5	25.5	81.1	−22.1
	(*1.5*)	(*2.5*)	(*2.2*)	(*5.3*)
light_F*CO_2_D	10.8	31.5	82.9	−16.7
	(*1.5*)	(*2.4*)	(*2.1*)	(*4.5*)
light_F*CO_2_E	7.4	29.1	80.6	−20.7
	(*1.4*)	(*2.3*)	(*2.0*)	(*4.2*)
light_G*CO_2_B	18.2	33.7	86.6	(−0.8
	(*1.7*)	(*3.1*)	(*2.4*)	) (*5.6*)
light_G*CO_2_C	17.0	31.4	85.6	−13.4
	(*1.6*)	(*2.7*)	(*2.2*)	(*4.6*)
light_G*CO_2_D	12.4	36.2	87.1	−9.1
	(*1.5*)	(*2.5*)	(*2.0*)	(*4.1*)
light_G*CO_2_E	10.9	37.7	84.1	−12.1
	(*1.5*)	(*2.4*)	(*1.9*)	(*3.6*)
light_H*CO_2_B	21.9	43.3	92.4	11.6
	(*1.4*)	(*2.9*)	(*2.0*)	(*4.8*)
light_H*CO_2_C	24.7	53.9	97.7	36.9
	(*1.3*)	(*2.4*)	(*1.7*)	(*4.0*)
light_H*CO_2_D	25.4	61.6	101.9	54.3
	(*1.2*)	(*2.2*)	(*1.5*)	(*3.2*)
light_H*CO_2_E	25.0	64.8	100.7	63.8
	(*1.2*)	(*2.1*)	(*1.5*)	(*3.0*)
light_I*CO_2_B	26.7	57.6	101.9	24.6
	(*1.1*)	(*2.0*)	(*1.5*)	(*3.7*)

light_I*CO_2_C	34.6	75.2	110.9	49.3
	(*1.0*)	(*1.3*)	(*1.2*)	(*2.8*)
light_I*CO_2_D	36.8	88.7	115.7	71.1
	(*0.9*)	(*1.2*)	(*1.0*)	(*2.0*)
light_I*CO_2_E	38.3	94.0	116.2	81.0
	(*0.9*)	(*1.1*)	(*0.9*)	(*1.7*)

Note: Standard errors of the coefficients were given in brackets. The insignificant coefficients are underlined, all other coefficients are significant at 0.05 level.

Table G2. Categorical regression results: the relationship between design element choice and greenhouse gas emissions.

Variable	**Design element choice**	**Jinshan**	**Langfang**	**Weifang**	**Pingliang**
Structure_A	*Multi- tunnel, 1 vent 10 m^{-2}*	*baseline choice*			
Structure_B	Multi- tunnel, 1 vent 20 m^{-2}	−8.0 (*0.1*)	−9.1 (*0.2*)	−8.5 (*0.1*)	−7.1 (*0.1*)
Structure_C	Multi- tunnel, 1 vent 30 m^{-2}	−12.6 (*0.1*)	−14.7 (*0.1*)	−13.7 (*0.1*)	−11.3 (*0.1*)
Structure_D	Venlo, 1 vent 10 m^{-2}	−5.8 (*0.1*)	−5.1 (*0.2*)	−5.1 (*0.2*)	−5.0 (*0.2*)
Structure_E	Venlo, 1 vent 20 m^{-2}	−13.2 (*0.1*)	−13.5 (*0.2*)	−13.1 (*0.1*)	−11.4 (*0.1*)
Structure_F	Venlo, 1 vent 30 m^{-2}	−17.5 (*0.1*)	−18.4 (*0.2*)	−17.5 (*0.1*)	−14.6 (*0.1*)
Cover_A	*Single PE film*	*baseline choice*			
Cover_B	Double PE film	6.9 (*0.0*)	10.8 (*0.1*)	9.0 (*0.1*)	7.0 (*0.1*)
Cooling_A	*No cooling*	*baseline choice*			
Cooling_B	Fogging: 200 g h^{-1} m^{-2}	0.0 (*0.1*)	0.5 (*0.1*)	0.1 (*0.1*)	0.1 (*0.1*)
Cooling_C	Fogging: 300 g h^{-1} m^{-2}	0.1 (*0.1*)	0.5 (*0.1*)	0.0 (*0.1*)	0.0 (*0.1*)
Cooling_D	Fogging: 400 g h^{-1} m^{-2}	0.1 (*0.1*)	0.5 (*0.1*)	0.0 (*0.1*)	0.2 (*0.1*)
Cooling_E	Pad and fan: 60 m^3 h^{-1} m^{-2}	10.2 (*0.1*)	12.0 (*0.2*)	11.1 (*0.1*)	10.3 (*0.2*)
Cooling_F	Pad and fan: 90 m^3 h^{-1} m^{-2}	15.0 (*0.1*)	18.4 (*0.2*)	16.7 (*0.1*)	15.0 (*0.2*)
Cooling_G	Pad and fan: 120 m^3 h^{-1} m^{-2}	20.1 (*0.1*)	24.7 (*0.2*)	22.8 (*0.2*)	20.0 (*0.2*)
Heating_A	*1.16 MW ha^{-1}*	*baseline choice*			
Heating_B	1.74 MW ha^{-1}	0.4 (*0.0*)	1.2 (*0.1*)	1.2 (*0.1*)	0.2 (*0.1*)
Heating_C	2.32 MW ha^{-1}	0.5 (*0.0*)	1.0 (*0.1*)	1.0 (*0.1*)	0.4 (*0.1*)
Thermal_screen_A	*No thermal screens*	*baseline choice*			
Thermal_screen_B	Transparent, 72% transimission	−21.4 (*0.1*)	−27.1 (*0.2*)	−27.1 (*0.1*)	−27.3 (*0.1*)
Thermal_screen_C	Non-transparent, white	−14.8 (*0.1*)	−7.2 (*0.2*)	−11.7 (*0.2*)	−13.5 (*0.2*)
Thermal_screen_D	Light blocking, one side black	−14.9 (*0.1*)	−9.7 (*0.2*)	−13.6 (*0.2*)	−13.1 (*0.2*)
Thermal_screen_E	Double-layer, top layer aluminized	−21.4 (*0.1*)	−27.1 (*0.2*)	−27.1 (*0.1*)	−27.3 (*0.1*)
Shade_screen_A	*No shade screens*	*baseline choice*			

Shading_screen_B	36% shading	−2. 5 (*0.0*)	−3.0 (*0.1*)	−3.3 (*0.1*)	0.0 (*0.1*)
Shading_screen_C	45% shading	−1.4 (*0.1*)	−0.3 (*0.1*)	−1.0 (*0.1*)	0.9 (*0.1*)
Shading_screen_D	56% shading	−1.4 (*0.1*)	−0.4 (*0.1*)	−1.0 (*0.1*)	1.0 (*0.1*)
Light_A	*No lighting*	*baseline choice*			
Light_B	HPS, 50 μmol m^{-2} s^{-1}	115.9 (*0.1*)	156.5 (*0.4*)	147.1 (*0.3*)	114.6 (*0.3*)
Light_C	HPS, 100 μmol m^{-2} s^{-1}	155.4 (*0.1*)	211.5 (*0.4*)	193.7 (*0.3*)	151.4 (*0.3*)
Light_D	HPS, 150 μmol m^{-2} s^{-1}	187.5 (*0.1*)	257.6 (*0.3*)	228.2 (*0.3*)	180.6 (*0.3*)
Light_E	HPS, 200 μmol m^{-2} s^{-1}	210.7 (*0.1*)	284.4 (*0.3*)	248.4 (*0.2*)	200.5 (*0.2*)
Light_F	LED, 50 μmol m^{-2} s^{-1}	99.2 (*0.1*)	133.8 (*0.4*)	128.2 (*0.3*)	101.1 (*0.3*)
Light_G	LED, 100 μmol m^{-2} s^{-1}	123.1 (*0.1*)	166.3 (*0.3*)	156.3 (*0.3*)	1227. (*0.3*)
Light_H	LED, 150 μmol m^{-2} s^{-1}	142.1 (*0.1*)	194.7 (*0.3*)	177.4 (*0.3*)	140.0 (*0.3*)
Light_I	LED, 200 μmol m^{-2} s^{-1}	155.8 (0.1)	211.0 (0.2)	189.9 (0.2)	151.7 (0.2)
CO_2_A	*No CO_2 enrichment*	*baseline choice*			
CO_2_B	50 kg CO_2 ha^{-1} h^{-1}	0.0 (0.1)	0.4 (0.2)	0.3 (0.1)	0.1 (0.2)
CO_2_C	100 kg CO_2 ha^{-1} h^{-1}	−0.1 (0.1)	0.6 (0.2)	0.4 (0.1)	0.3 (0.2)
CO_2_D	150 kg CO_2 ha^{-1} h^{-1}	0.0 (0.1)	0.3 (0.2)	0.5 (0.1)	0.2 (0.1)
CO_2_E	200 kg CO_2 ha^{-1} h^{-1}	0.1 (0.1)	0.6 (0.2)	0.4 (0.1)	0.5 (0.1)
Whitewash_A	*No whitewash*	*baseline choice*			
Whitewash_B	50% transmission	3.5 (0.0)	7.76 (0.0)	6.78 (0.0)	5.80 (0.0)

Note: Standard errors of the coefficients were given in brackets. The insignificant coefficients are underlined, all other coefficients are significant at 0.05 level.

Chapter 4 Greenhouse investment decisions under price and policy uncertainty

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Abstract

Uncertainty in output prices and the potential phasing-out of the subsidy scheme could jointly affect the optimal timing of greenhouse investment in China. Accounting for price and policy uncertainty simultaneously, this study employed a real options approach and formulated the investment decision as an optimal stopping problem. The least squares Monte Carlo method was used to approximate the optimal investment timing and the value of waiting under various combinations of subsidy level, subsidy termination risk factor, and tomato price evolution process. The numerical illustration shows that uncertainty about the phasing-out of the subsidy scheme can significantly reduce the value of waiting and induce earlier investment. In addition, an increase in the subsidy level could reduce the value of waiting and encourage earlier investment. A combination of a high subsidy level and the signalling of subsidy termination can substantially reduce the value of waiting and create a strong incentive for early investment.

Keywords

Investment decision, real options, policy uncertainty, subsidy policy, greenhouse horticulture

4.1 Introduction

Under China's "vegetable basket" policy, local governments are incentivised to transform local food production into more productive and safer systems (Zhong et al., 2020). Greenhouses, offering high efficiency in land, water and chemical use, as well as higher crop yields compared to field production (Zhou et al., 2021), can be a key solution to provide cities with year-round supply of fresh produce.

However, greenhouse investments are capital-intensive. A 1-hectare Venlo-type greenhouse, for example, can cost over 1 million RMB (around 125,000 €). In China, many greenhouse projects are funded through matching contributions from the central government, local governments, and agribusiness firms (Gong & Zhang, 2016). In Beijing, district-level governments provide subsidies covering 30% of greenhouse construction costs, and municipal governments offer an additional 20% for eligible projects (Beijing Municipal Bureau of Agriculture and Rural Affairs, 2022). The remaining funds come from the greenhouse firms themselves. These subsidies play a significant role in improving the economic feasibility of greenhouse investments. In some regions of China, a 50% subsidy can turn a greenhouse investment from unprofitable to profitable (Min et al., 2022).

In 2023, the Chinese government introduced its first national development plan for the horticultural sector. The plan focuses on three key areas: encourage new greenhouse investments, upscale production, and modernize existing infrastructure. A specific target has been set to increase the percentage of vegetables supplied by greenhouses from 30% to 40% by 2030. To achieve this, the plan calls for the construction of over 200 high-tech greenhouses and protected agricultural parks, primarily in the suburbs of major cities (MOA et al., 2023). Along with this development plan, the government plans to allocate additional fiscal resources to the greenhouse sector through various channels.

The use of government subsidies has long been an important tool to achieve industrial development goals in China (Gong & Zhang, 2017; Yang et al., 2016). However, these subsidy programs in China typically have a limited duration. For example, the first phase of the electric vehicle subsidy program was introduced in 2009 and ended in 2012 (Hao et al., 2014). Similarly, the renewable energy sector received substantial subsidies from 2006 to 2014, but subsidy levels began to decrease in 2015 and were completely eliminated for new projects in 2021 (Zhao et al., 2022). Given these precedents, it is reasonable to anticipate that the current subsidies for the greenhouse sector will also be phased out once the goals outlined in the 2023 development plan are achieved. This raises an important question: How will the uncertainty about the phasing-out of subsidy programs affect the decision-making of potential investors in China's greenhouse sector?

Previous studies have assessed the economic feasibility of greenhouse investments in China. For example, Min et al. (2022) evaluated the distribution of the Net Present Value (NPV) for an investment in a greenhouse for tomato production, taking into account price uncertainty in both inputs and outputs using Monte-Carlo simulation. However, this study largely overlooked the uncertainty related to subsidy policies. In scenarios where both price and subsidy policy uncertainty exist, traditional capital budgeting methods—which typically view investments as "now or never" decisions—may fail to fully account for investors' strategic considerations. The real option approach (ROA) recognizes the value of flexible decision-making under uncertain environments and provides a useful framework for addressing investment problems with multiple sources of uncertainty.

ROA began with the seminal works of Arrow & Fisher (1974) and Henry (1974), and has gradually found applications in agricultural investment problems. Applications of ROA in agriculture have mainly focused on uncertainty related to economic aspects, modelling factors such as input and output prices or investment returns as stochastic processes (e.g., Frey et al., 2013; Luong & Tauer, 2006; Musshoff, 2012; Schulte et al., 2018; Smith, 2018; Spiegel et al., 2021). A number of studies have also employed ROA to assess the impact of agricultural policies. For example, Feil et al. (2013) compared the impact of price floors, investment subsidies, and production ceilings on agricultural investment in competitive markets. Di Corato & Zormpas (2022) explored how the European Union's decoupled payments affect farmers' investment decisions. However, these studies generally assume static policy environments, i.e., they do not take into account uncertainty about future policy changes. As a result, their focus is mainly on price or production uncertainty, rather than uncertainty directly related to evolving policies.

Only a handful of studies have explicitly examined how policy uncertainty affects agricultural investment decisions. Purvis et al. (1995) were among the first to apply ROA to examine policy uncertainty within the agricultural sector. They analyzed investment in free-stall facilities on dairy farms under uncertain environmental regulations. Their model assumed a normally distributed random component of the investment costs to account for changes in environmental compliance requirements. Floridi et al. (2013) studied the adoption of automatic milking systems under uncertain subsidy schemes with a simple two-period model. They modelled subsidy amounts as a Wiener process and concluded that higher uncertainty leads to delayed adoption. More recently, Yanore et al. (2023a) analyzed the production expansion strategies of Dutch dairy farmers in the face of uncertainty about the implementation of a phosphate emission right system. In their model, policy uncertainty was represented in a straightforward way, with either the probability of policy implementation or the timing of policy introduction fixed. The NPVs of investing and waiting were compared under different scenarios.

While a common insight of real options theory is that higher levels of uncertainty usually increase the value of waiting and thus lead to a delayed investment, this is not always the case. Sarkar (2000) found that for low-growth and low-risk projects, increased volatility in investment returns can actually increase the probability of investing. Yanore et al. (2023a) showed that when farmers expect a delayed introduction of the phosphate emission right system, the optimal investment strategy is to expand production. The modelling of the underlying stochastic process can also affect the timing of investment.

In essence, ROA treats dynamic investment decisions as optimal timing problems (Wesseler & Zhao, 2019). The interactions between price and policy uncertainty can affect the optimal timing of investments, potentially pushing it in opposite directions. The optimal timing depends on trade-offs between the lost profits during waiting compared to the risks of losing subsidies if the subsidy policy is abolished. To our knowledge, no study has explored the interactions between these two effects in the agricultural context.

The aim of this study is to examine the impact of uncertainty about output prices and the phasing-out of subsidy policies on the timing of investment in greenhouses in China. This research seeks to fill a gap in the literature on agricultural investment, in particular the limited understanding of the interactions between price and policy uncertainty. Through numerical illustration, the study identifies the conditions under which tomato prices, subsidy levels, and investors' expectation on the duration of subsidy schemes, may lead to a postponed investment in greenhouses in China.

The remainder of this paper is organized as follows: Section 2 presents the analytical framework. It explains how the price and policy uncertainty was modelled and describes how the optimal investment timing and the value of waiting were calculated using the Least squares Monte Carlo (LSM) algorithm. Section 3 provides a numeric illustration under different combinations of parameters related to price and policy uncertainty. The paper ends with conclusions and discussion.

4.2 Analytical framework

4.2.1 Description of the investment problem

This paper assumes that an investor can flexibly determine the timing of investment in a greenhouse over a time horizon of T years. Once the investment is made, the greenhouse project can operate for a lifetime of L years. The payoff of the investment made at year t can be calculated as:

$$V_t = -\frac{I_t}{(1+r)^t} + \sum_{l=t}^{t+L} \frac{CF_l}{(1+r)^{l+1}} \tag{4.1}$$

where r is the discount rate, I_t is the initial investment outlay at time t. The value of I_t is dependent on the existence of the subsidy scheme at time t. CF_t is the cash flow generated in year t. At each time point, the investor is aware of the past market and policy conditions but has no information on the future market and policy conditions. At each time point, the investor decides whether to invest or (continue to) delay the investment. The investor needs to choose the optimal timing t^* of the investment that maximizes the value of investment V_{t^*}. The value of waiting W at $t = 0$ is the difference between the investment value determined by the ROA and the value of investing at $t = 0$:

$$W = \max\{V_{t^*} - V_0, 0\} \tag{4.2}$$

4.2.2 Uncertainty about subsidy policy

In our model, we accounted for the uncertainty associated with the termination of the existing subsidy scheme. A sudden termination of a subsidy scheme can be modelled as a jump process (Boomsma & Linnerud, 2015; Dixit & Pindyck, 1994). The change in the investment outlay, denoted as dI, is given by:

$$dI = \begin{cases} 0 & \text{with probability} \quad 1 - \lambda dt \\ sI_0 & \text{with probability} \quad \lambda dt \end{cases} \tag{4.3}$$

where s is the level of subsidy and is a fraction between 0 and 1. λ denotes the subsidy termination risk factor. The probability that a subsidy termination occurs within a short time interval dt is λdt. The subsidy scheme is in effect at the beginning of the investment horizon t_0, the actual investment outlay at that moment is $(1 - s)I_0$. If termination occurs, the investment outlay will increase by sI_0, representing the lost subsidy. We assume that a subsidy scheme is not reintroduced after it has been terminated.

4.2.3 Stochastic tomato price

The choice of stochastic process of a specific commodity price is not straightforward. Both geometric Brownian motion (GBM) and mean-reversion (MR) are commonly used stochastic diffusion processes for real options valuation (Bastian-Pinto et al., 2021). GMB has been used to model the prices of various agricultural products, including crops (Di Corato & Zormpas, 2022), sugar (Smith, 2018), wheat (Tozer, 2009), milk (Tauer, 2006), and coffee (Luong & Tauer, 2006).

Some researchers claim that MR is more appropriate for modelling prices of agricultural products, as in the long term, prices of agricultural products should converge to the marginal costs of production (Bastian-Pinto et al., 2021; Bessembinder et al., 1995). MR has been used to model prices for coppice biomass price (Spiegel et al., 2020), milk (Schulte et al., 2018), and the overall farm revenue (Delbridge & King, 2016; Sanderson et al., 2016).

Either GBM or MR have elements of truth in commodity prices, using either model for a specific commodity may be too simplistic (Bastian-Pinto et al., 2021). A model that captures both the “random walk” and “mean-reverting” effects may offer a more realistic representation of commodity prices (Schwartz & Smith, 2000). Following Linnerud et al. (2014), we model the monthly tomato price process as

$$dP_{it} = \alpha P_{it} dt + \eta(\bar{P}_i - P_i)dt + \sigma P_{it} dB_t \tag{4.4}$$

where P_{it} represents the tomato price of month i in year t; α is the drift rate, reflecting the expected price trend compared with the previous year. η is the speed of reversion, $\bar{P}_i$ is the "normal" price level to which the tomato price tends to revert. σ is the volatility rate, it captures price variation. W_t is the standard Brownian motion, $B_t = \varepsilon\sqrt{dt}$, ε is a standard normal distribution. When η is zero, the price follows a GBM. When $0 < \eta < 1$ and $\alpha \neq 0$, the price follows a MR process with trend.

4.2.4 Value of waiting and the optimal investment timing

It becomes difficult to derive an analytical solution to the optimal stopping problem when multiple sources of uncertainty exist. Therefore, we used the Least Squares Monte Carlo (LSM) method to approximate the optimal investment timing and the option value (Longstaff & Schwartz, 2001). The LSM method is a backward dynamic programming algorithm that starts at the final decision point and works backwards. The objective of the LSM algorithm is to provide a pathwise approximation to the optimal stopping rule that maximizes the option value. The option value is the sum of the payoff of investing at $t = 0$ (V_0) and the value of waiting at $t = 0$ (W). In the following analysis, we will focus on the value of waiting. The procedure of the LSM algorithm is as follows:

Price simulation. We started by simulating the tomato price and subsidy continuation processes. We generated 10,000 paths for future tomato prices as defined by Eq. (4.4) and the subsidy continuation process as defined by Eq. (4.3). These simulations covered a time horizon of $T + L$ years, with a time-discretization of 1 year.

Valuation procedure. At the final decision point T, the algorithm evaluates whether the investment is in the money ($V_T > I_T$) for each simulation path. The algorithm then proceeds to the previous decision point and checks the optimal exercise policy at $T - 1$. Here, the investor can choose either to invest immediately or to wait and revisit the decision at the next point T. The optimal exercise policy is determined by comparing the payoff from investing at $T - 1$ (V_{T-1}) with the expected continuation value (C_{T-1}).

Estimation of continuation value. The expected continuation value is estimated using least squares regression to approximate the conditional expectation function. More specifically, the algorithm used a third-degree polynomial regression on the current project values. Only in-the-money paths were used for running the regression, as recommended by Longstaff & Schwartz, (2001). After determining the coefficients of the conditional expectation function, the continuation value at $T - 1$ can be predicted using these estimated coefficients. The result of the least squares regression is an efficient, unbiased estimator of the conditional expectation function (Longstaff & Schwartz, 2001).

Optimal stopping. If the estimated continuation value is smaller than the immediate exercise payoff, then the optimal exercise policy at $T-1$ is to invest. The payoff at $T-1$ is updated to V_{T-1}, and the subsequent payoffs along the same path are set to zero. Otherwise, the payoff at $T-1$ is zero and the remaining payoffs along the same path are left unchanged. The recursion proceeds backwards until the exercise decisions at each discrete time point along each path have been determined.

Optimal timing of investment and value of waiting. The optimal timing of investment $\overline{t^*}$ is the average optimal investment timing over all paths. The expected value of waiting $\overline{W}$ is the average of the difference between the discounted maximum investment payoffs V_{t^*} and the value of investing at $t = 0$ (V_0) over all paths.

4.3 Numerical illustration

This section first provides the parameters used in the numerical illustration. Sections 4.3.2 to 4.3.4 present the results of the numerical illustration. We begin by exploring the impact of subsidy termination risk on the investment decision, specifically looking at how variations in the subsidy termination risk factor λ affect the optimal timing t^* and the value of waiting $\overline{W}$. After that, we explore the impact of different subsidy levels s on the expected waiting value and optimal investment timing. Finally, we discuss how the evolution of tomato prices interacts with the subsidy termination risk to collectively shape investment decisions.

4.3.1 Parametrization

The default value of s was set at 0.3, aligning with the typical 30% subsidy offered to new greenhouse projects in China. For the numerical illustration, the value of s was varied within the range of 0 to 0.5. The occurrence of an event in a jump process follows a Poisson distribution. The expected duration of the subsidy scheme is $\frac{1}{\lambda}$. Since there is no objective measure for the likelihood of subsidy termination, $\frac{1}{\lambda}$ reflects the investor's subjective expectation of the duration of the subsidy scheme. We varied the value of λ between 0 and 0.4, which corresponds to an expected duration of the subsidy scheme ranging from an indefinite period to as short as 2.5 years.

The ideal approach for parameterizing the model in Eq. (4.4) would be to statistically estimate these parameters using multi-year historical price series. Unfortunately, historical price data of sufficient length for parameter estimation are not available, especially not for specific greenhouse tomato varieties. GBM appears suitable for modelling tomato prices, especially given an observed upward trend in vegetable prices in China (Li & Zhang, 2013; Xiong et al., 2018; Xu et al., 2017), as shown in Figure 4.1. Xiong et al. (2018) attribute the growth of vegetable prices to inflation. In our model, the default value for α was set to 0.03, aligning with the inflation target set by the Chinese government for 2023, which implies that tomato prices remain fixed in real terms.

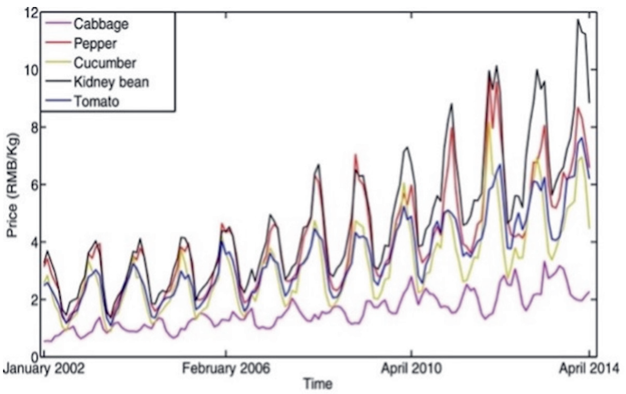

Figure 4.1. Five vegetable price series in China, from Xiong et al. (2018).

The value of σ was set at 0.25, an average estimate derived from volatility rates for other agricultural products. For example, the volatility was 0.2963 for soy and 0.2941 for castor in Brazil (Brandão et al., 2013). In the United States, the estimated volatilities for soybean were 0.1926 when modelled as GBM and 0.1941 under MR. For cotton, they were 0.2537 when modelled as GBM and 0.2557 when modelled as MR (Bastian-Pinto et al., 2021). For sugar in the US, it was 0.2512 when modeled as GBM (Smith, 2018). The estimated volatility for wheat in Australia under GBM was 0.2441 (Tozer, 2009).

To investigate whether the impact of policy uncertainty varies under different tomato price processes, we also examined scenarios incorporating a mean-reverting component into the tomato price models. A η value of 0.1 implies that any deviation of the tomato price from the normal price level would be corrected by 10%. In the numerical illustration, the value of η was varied between 0 and 0.2.

Table 4.1 summarizes the parameter values or ranges thereof used in the numerical illustration. The initial investment costs, monthly yield and variable costs that are needed for calculating the yearly net cash flow, and discount rate are taken from Min et al. (2023).

Table 4.1. Overview of parameter values or ranges.

Parameter	Description	Value or range	Remark or source
Cash flow			
I_0	Initial investment outlay	1056.5 ¥ m^{-2}	Min et al. (2023)
P_{i0}	2021 Monthly tomato prices		Min et al. (2023)
CF	Yearly net cash flow		Min et al. (2023)
r	Discount rate	6.1%	Min et al. (2023)
Price uncertainty			
α	Drift rate	0 – 0.04	Varied around the inflation target of 0.03
η	Mean reversion factor	0 – 0.2	A η value of 0.1 means the tomato price will adjust back towards its normal level by 10%.
σ	Volatility	0.25	Based on Bastian-Pinto et al. (2021), Brandão et al. (2013), Smith (2018), Tozer (2009)
Policy uncertainty			
s	Subsidy level	0 to 0.5	Varied around the current subsidy level of 0.3
λ	Subsidy termination risk factor	$\rightarrow$0 to 0.4	The expected duration of the subsidy scheme ranges from indefinite to 2.5 years
Time horizon			
T	Investment horizon	10 years	Authors' assumption.
L	Lifetime of a greenhouse	20 years	The average lifetime of a glasshouse is 20 years

4.3.1 Effect of subsidy termination risk

Figure 4.2 shows the optimal timing of investment t^* and the expected waiting value $\overline{W}$ for various combinations of subsidy termination risk factor (λ) and drift rate (α) of tomato prices. These calculations assume fixed values for $\eta = 0$, $\sigma = 0.25$, $s = 0.3$, suggesting that monthly tomato price is modelled as a geometric Brownian motion.

When there is no risk of subsidy phasing-out ($\lambda \rightarrow 0$), an increase in drift rate α can lead to a significant increase in both the optimal timing of investment and the value of waiting. This suggests that investors anticipating an upward trend in tomato prices are more likely to delay their investment decisions. In particular, when α is set at 0.03, in line with the inflation target, investors may delay their investment by up to 5.2 years.

When uncertainty about the phasing-out of the subsidy scheme is introduced, the value of waiting is significantly reduced, leading to earlier investment. For example, under a positive price trend ($\alpha = 0.03$), if the investor has a subjective expectation that the expected duration of the subsidy scheme is 10 years ($\lambda = 0.1$), t^* decreases from 5.2 years to 2.2 years, and $\overline{W}$ decreases from 259 ¥ m^{-2} to 133 ¥ m^{-2}. As λ increases, these figures continue to decrease. When the expected duration of the subsidy scheme is reduced to 5 years ($\lambda = 0.2$), t^* and $\overline{W}$ decrease to 0.8 years and 99 ¥ m^{-2}, respectively. This suggests that when investors anticipate the risk of subsidy phasing-out, they are more likely to invest earlier to avoid the potential loss of subsidy.

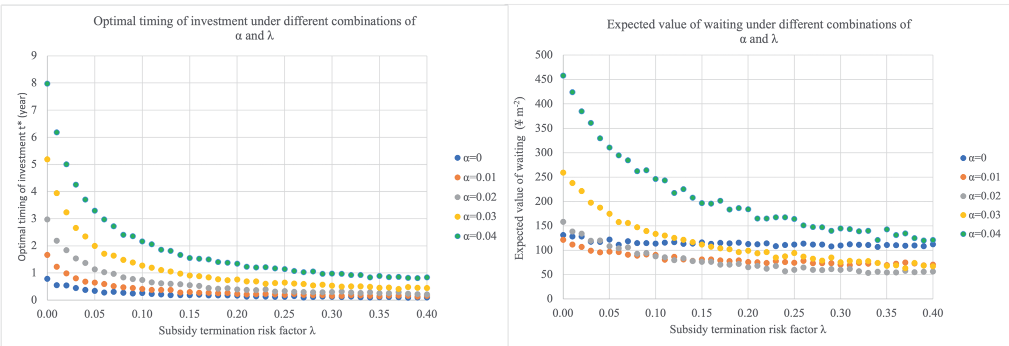

Figure 4.2 The optimal investment timing t^* and the value of waiting $\overline{W}$ for different combinations of drift rate α and subsidy termination risk factor λ ($\eta = 0$, $\sigma = 0.25$, $s = 0.3$).

4.3.1 Effect of subsidy levels

Figure 4.3 displays the optimal timing of investment t^* and the expected value of waiting $\overline{W}$ for various combinations of subsidy level (s) and subsidy termination risk factor (λ), while keeping α at 0.03, $\eta = 0$, and σ at 0.25.

As the level of subsidy s increases, both $\overline{W}$ and t^* decrease. With a positive price trend ($\alpha = 0.03$), if s is low, say 0.1, even a high subsidy termination risk factor ($\lambda = 0.3$) cannot fully offset the value of waiting caused by the upward trend in tomato price. In such cases, the investor may defer the investment decision for approximately 3 years. If s increases to 0.5, t^* is reduced from 2.8 years to 0.1 years. Furthermore, given the same value of λ, the marginal impact of raising s on reducing $\overline{W}$ and t^* is more significant when starting from a lower level of subsidy. For a given value of λ, the decline in $\overline{W}$ and t^* caused by increasing s from 0.1 to 0.2 is greater than the corresponding reduction achieved by increasing s from 0.4 to 0.5.

The impact of subsidy levels on reducing the value of waiting is more pronounced when it is combined with the risk of the phasing-out of the current subsidy scheme. In scenarios without the risk of subsidy phasing-out, an increase in s from 0.1 to 0.5 results in a decline in $\overline{W}$ from 359 ¥ m^{-2} to 201 ¥ m^{-2} — a decrease of 158 ¥ m^{-2}. When there is a risk of subsidy termination (λ = 0.1), changing s from 0.1 to 0.5 results in $\overline{W}$ dropping from 277 ¥ m^{-2} to 72 ¥ m^{-2}, a reduction of 205 ¥ m^{-2}

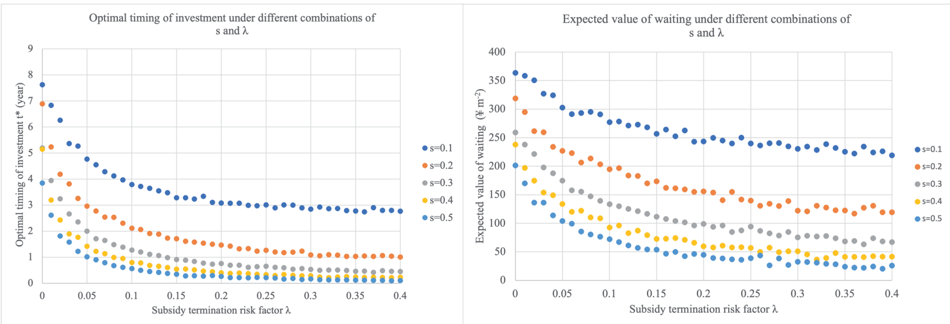

Figure 4.3. The optimal investment timing t^* and the value of waiting $\overline{W}$ for different combinations of subsidy level s and subsidy termination risk factor λ ($\eta = 0$, $\sigma = 0.25$, $\lambda = 0.1$).

4.3.1 Effect of tomato price evolution

Figure 4.4 shows the optimal timing of investment t^* and the expected value of waiting $\overline{W}$ for various combinations of the mean reversion factor (η) of tomato prices and the subsidy termination risk factor (λ), while keeping α at 0.03, σ at 0.25, and s at 0.3.

Compared to a GBM model of tomato prices where $\eta = 0$, the inclusion of a very small mean-reversion component in tomato prices can significantly reduce the value of waiting. As the mean reversion factor η increases, both $\overline{W}$ and t^* decrease. For instance, keeping λ at 0.1, when η increases from 0.05 to 0.1, $\overline{W}$ diminishes from 29 ¥ m^{-2} to 0.3 ¥ m^{-2}. In such conditions, the value of waiting almost vanishes, making immediate investment a more favourable choice. This implies that if an investor believes that tomato prices will fluctuate around their normal level, they will have a lower value of waiting and would be inclined to invest earlier.

However, it is important to note that the potential uncertainty about the phasing-out of the subsidy scheme can still reduce both $\overline{W}$ and t^*, whether the monthly tomato price is characterized by a GBM or a mean reverting process.

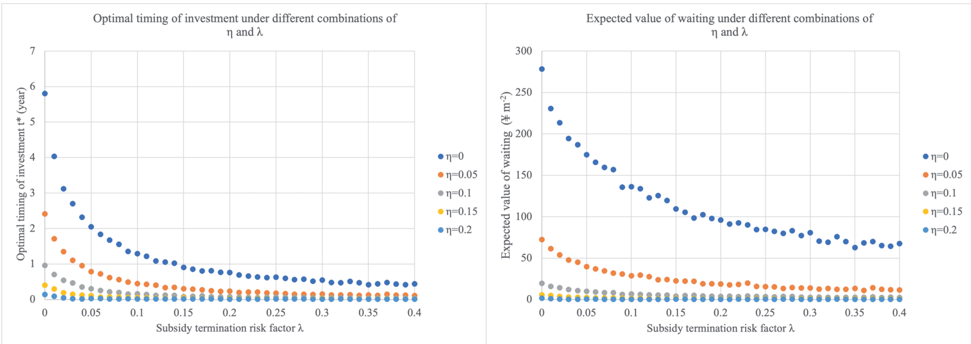

Figure 4.4. The optimal investment timing t^* and the value of waiting $\overline{W}$ for different combinations of mean version factor η and subsidy termination risk factor λ ($\alpha = 0.03$, $\sigma = 0.25$, $s = 0.3$).

4.4 Conclusions and discussion

The purpose of this study was to examine how uncertainty in output prices and the potential phasing-out of the subsidy scheme affect the timing of greenhouse investments in China. We represented the continuity of the subsidy scheme as a jump process and modelled the tomato price with two stochastic processes: a geometric Brownian motion and a mean reverting process. Using the real options approach, the investment problem was formulated as an optimal stopping problem and was solved using the Least Squares Monte Carlo method. Through numerical illustration, we showed how the optimal timing of investment and the value of waiting vary under various combinations of parameters tied to price and policy uncertainty. These parameters reflect the investors' expectations about the future evolution of tomato prices and subsidy policies. Our results identified the critical parameter values that could either delay or accelerate an investment.

The main findings of this study can be summarised as follows. First, uncertainty about the phasing-out of the subsidy scheme can significantly reduce the value of waiting and induces investors to invest earlier. Second, an increase in the subsidy level could also reduce the value of waiting and encourage earlier investment, even without the risk of the subsidy being terminated. The marginal impact of raising the subsidy level is more pronounced when starting from a lower initial subsidy level. Third, the combination of a high subsidy level and the signalling of subsidy termination could greatly reduce the value of waiting and prompt immediate investment.

This work contributes to the literature by simultaneously accounting for both price and policy uncertainty, two prevalent sources of uncertainty in agricultural investment that have not been jointly considered in previous ROA applications in agriculture. Contrary to earlier studies that concluded policy uncertainty generally leads to delayed investment (Floridi et al., 2013; Purvis et al., 1995), our findings suggest that it can also induce earlier investment, a conclusion that aligns with Yanore et al. (2023a). Compared to previous research, our analysis accounts for price and policy uncertainty simultaneously, offering insights into how the timing of a sudden policy change interacts with subsidy levels and price uncertainty to jointly determine the optimal timing of investment.

The findings of this study provide valuable insights for policy makers. When designing subsidy policies, policy makers could influence the pace of greenhouse investments in two ways: by altering the level of subsidies or by influencing investors' expectations about the duration of the current subsidy scheme. Policy makers need to decide carefully how much information to disclose about future subsidy plans, as uncertainty of subsidy policies can significantly affect the timing of investment. On one hand, to achieve sector development goals within a specific timeframe, they can encourage early investment by increasing subsidy levels and signalling a potential phasing-out of the program. On the other hand, to prevent premature investment in immature markets, policy makers can foster stable expectations among investors by clearly stating the conditions or timeframe for the phasing-out of subsidies, or by confirming that the subsidy scheme will continue if it is intended to be permanent.

As is common in real options analysis, the valuation outcomes in this study are sensitive to the values of various parameters. In our numerical illustration, the parameters related to price uncertainty were varied within a range of possible values based on literature or the inflation target. While policy uncertainty cannot be objectively quantified, it is the investors' subjective expectations about this uncertainty that determines their decision-making (Hardaker & Lien, 2010). In our model, the subsidy termination risk factor λ was varied within a range from 0 to 0.4. This range reflects the expected duration of the subsidy scheme ranging from an infinite period to as short as 2.5 years. Future research could enhance this part by incorporating Chinese greenhouse investors' subjective probabilities regarding the phasing-out of the subsidy scheme. The subjective probabilities of investors could be elicited using one of the methods suggested by Norris & Kramer (1990).

This study approaches the investment problem from a normative perspective, assuming that investors have high degrees of rationality and can correctly determine the optimal timing of investment based on the expectation of discounted future payoffs. An alternative approach is to adopt a descriptive perspective, incorporating more realistic assumptions about investor behaviour, as noted by Miller & Shapira (2004). Improving our understanding of the implications of bounded rationality, information imperfection, and behavioural biases could bring the real options model closer to the real-world investment context (Trigeorgis & Reuer, 2017). Recent studies have begun to explore the impact of risk preferences within the framework of real option analysis. For instance, Yanore et al. (2023) accounted for farmers' risk preferences by adding a risk premium to the risk-free discount rate. Spiegel et al. (2021) found that higher levels of risk aversion can lead to earlier but smaller-scale adoption of agricultural technology. According to Menapace et al. (2013), decision-makers' risk preferences and subjective probabilities of uncertain events are likely to be interrelated. If this is true, these factors would collectively influence the optimal timing of investment, a topic warranting further research. Apart from risk preferences, future studies could also examine how time preferences affect investment decisions under price and policy uncertainty. Researchers could consider using hyperbolic discounting rather than exponential discounting.

Chapter 5 Evaluating the adoption of sensor and robotic technologies from a multi-stakeholder perspective: the case of greenhouse sector in China

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Abstract

This study evaluates sensor and robotic technologies that are driving the digitalisation and automation transition of the greenhouse sector in China. To bridge the gap between technology assessment and innovation adoption, the evaluation framework used the technology attributes defined in the Diffusion of Innovation theory, and involved multiple stakeholder groups: growers, investors, technology suppliers and policy makers. The Bayesian best-worst method was used to elicit stakeholder preferences and expert-rated technology scores for each attribute. Combining the two produced a probabilistic performance score for each technology. The results highlighted the heterogeneous preferences of different stakeholder groups. The leaf temperature sensor received the highest score among growers and policy makers. Investors and technology suppliers favored the scouting and harvesting robots, respectively. These findings underscore the importance of tailoring strategies to promote technologies that align with the specific priorities of each stakeholder group.

Keywords

Adoption, Technology assessment, Agricultural innovation, Stakeholder, Best-worst method

5.1 Introduction

The agricultural sector is currently undergoing a rapid transition towards increased digitalisation and automation (King, 2017; Saiz-Rubio & Rovira-Más, 2020; Verdouw et al., 2021). This transition is described using various terms, including smart farming (Regan, 2019; Verdouw et al., 2021), digital farming (Shamshiri et al., 2018), and agriculture 5.0 (Saiz-Rubio & Rovira-Más, 2020). Regardless of the terminology used, the underlying digitalisation and automation technologies remain similar across application domains, i.e. (i) sensors and the Internet of Things for data collection, (ii) data platforms and cloud management for data storage and analytics, (iii) artificial intelligence for advanced planning and optimisation, and (iv) automation technologies for replacing human labour and executing physical tasks (Ehlers et al., 2022; Shamshiri et al., 2018). The transition towards digitalisation and automation is particularly evident in greenhouse production systems, which are designed as relatively closed environments for climate control, with the help of various equipment and technologies (Verdouw et al., 2014).

Technology innovation in the horticultural sector has witnessed considerable progress in recent years. Sensors that directly monitor the status of plants (e.g., sap flow, leaf photosynthesis) are available on the market (van Straten et al., 2010). In addition, robotics for leaf removal (Van Henten et al., 2006), targeted spraying for pest control (Dai et al., 2022; Sammons et al., 2005), and harvesting (Bac et al., 2014) have been developed and tested in some exploratory cases. However, the adoption of these technologies by greenhouse producers has been very limited (Bac et al., 2014; Hemming, 2020).

A possible reason for the limited adoption of digitalisation and automation technologies could be the weak role of adopter preferences in the innovation process. Technologies should be evaluated not only on their performance on a given criterion, but also on the extent to which the adopter values that criterion (de Oca Munguia & Llewellyn, 2020; Geisler, 2002). However, in existing agricultural innovation studies, there is often a separation between invention and adoption. The focus of technology assessment studies is typically on the functionality of technology, while the users of the technology remain largely invisible (McCampbell et al., 2023). On the other hand, in the agricultural innovation adoption literature, researchers have often focused solely on the adopter's characteristics and the general farming context, and less on the attributes of the technology itself (Shang et al., 2021).

To bridge the gap between technology characteristics and adopters' characteristics, the diffusion of innovation (DOI) theory offers a potential solution. The DOI theory recognizes that it is not only the characteristics of the innovation itself, but rather the adopters' perceptions of the technology attributes that significantly influence its adoption 30/11/2023 14:11:00. Furthermore, innovation is a coevolution process with a lot of feedback in which many different actors at various levels play a role (Smits & Den Hertog, 2007). Therefore, it is essential to extend the focus beyond technology adopters and consider a broader range of stakeholders in the technology adoption and diffusion process (Alcon et al., 2014; Moretti et al., 2023; Yazdani et al., 2023). This includes growers, investors, technology suppliers, and policy makers, who collectively drive the adoption process in the greenhouse sector in China (Gomes et al., 2018).

In China, ***growers*** are merely involved in management activities and do not have ownership of the greenhouse units. Their responsibilities encompass analyzing data produced by sensors and climate computers, optimizing the greenhouse environment, conducting regular crop scouting and registration, and making cultivation decisions such as de-leafing, harvesting, and crop protection. Growers' goal is to increase greenhouse production and achieve higher economic returns. An innovation will diffuse only if information about its use-value characteristics is transmitted to the potential users (Lundvall, 2016). Growers could act as end-users, modifiers, designers, and also as opponents of innovative technologies, and thus have a significant influence on the diffusion process of digital greenhouse technologies (Oudshoorn & Pinch, 2003).

Due to the high investment costs, high-tech greenhouse ***investors*** in China are usually run by agricultural companies, rather than households. Many of the high-tech greenhouse companies in China do not have an agricultural background but instead come from the real estate, construction, or information technology sectors (Wang et al., 2023). These investors typically do not directly participate in the management of greenhouse operations. Instead, they serve as providers of funds and hold ownership of the greenhouse assets.

Greenhouse horticulture is a typically supplier-dominated sector, where research and development (R&D) is mainly performed and diffused by ***technology supplier*****s** and public-funded research and extension services (Berkers & Geels, 2011; Pavitt, 1984). Private agricultural R&D investment has grown rapidly since 2000 (Hu et al., 2011). In addition to selling products, technology suppliers offer training and post-installation technical support. They maintain direct contact with investors and growers, closely monitor the implementation of their products in greenhouses, and gather feedback on implementation experiences from growers. When problems occur, growers often turn to technology suppliers for solutions.

Finally, ***policy makers*** play a crucial role in the greenhouse sector in various ways. Firstly, universities and research institutions, among other public entities, serve as primary sources of agricultural innovation in China, and policy makers can steer the direction of R&D in the agricultural sector (Hu et al., 2011). The 14th Five-Year Plan for agriculture modernization of China has identified sensors and robotics technologies as key R&D areas in the agricultural sector (MOA, 2021). Secondly, policy makers can accelerate the adoption of technologies by designing subsidy schemes (e.g., deciding which technologies are eligible for subsidy), allocating funds to project-based development programs, facilitating land leasing, or providing training or demonstration programs on digital technologies (Zhong et al., 2020). Thirdly, policy makers can act as joint investors of greenhouse projects in China (Gong & Huang, 2016).

The objective of this study is to analyze the preferences of different stakeholder groups in the Chinese greenhouse sector for different innovative greenhouse technologies. The paper defines each technology in terms of six attributes of innovation defined in the DOI, i.e., cost-benefit, environmental impact, trialability, observability, complexity, and compatibility, as important explanations of adoption. Next, it uses the Bayesian Best-Worst (Bayesian BWM) method to determine the preferences of stakeholders for the different attributes. This information is combined with attribute scores for each technology which were obtained through expert elicitation. Finally, a composite overall performance score was calculated for each technology, by multiplying the stakeholder weights with the attribute scores.

5.2 Evaluation framework

In the evaluation framework, we aim to link the technology and stakeholder dimensions. The evaluation framework consists of two stages (see Figure 5.1). The first stage is the elicitation of the relative importance of the attributes of technologies from four groups of stakeholders: growers, investors, technology suppliers, and policy makers. In the second stage, technical experts were employed to elicit the performance score of technology on the identified attributes.

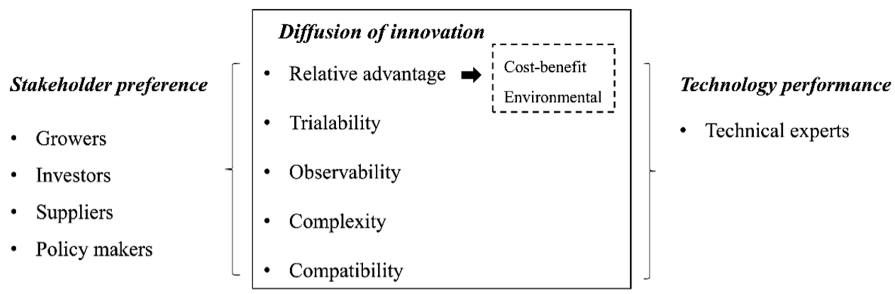

Figure 5.1. Evaluation framework.

The evaluation framework defines the evaluation criteria based on the Diffusion of Innovation of Rogers (1962), a widely adopted theory in agricultural innovation adoption studies. DOI identified five perceived attributes of an innovation: relative advantage, *complexity*, *compatibility*, *trialability*, and *observability*, as important explanations of adoption. In this evaluation framework, relative advantage is decomposed into *cost-benefit* and *environmental impacts*. Cost-benefit is further decomposed into three sub-criteria: *initial investment*, cost *reduction*, and *revenue increase*. An overview of the description for each evaluation criterion is shown in Table 5.1.

Table 5.1. Description of the evaluation criteria situated for greenhouse production.

Criteria	Description
Cost-benefit (C_1)	The initial investment to obtain the technology, the reduction in operational costs, and the increase in revenue as a result of using the technology.
Initial investment (C_{11})	The initial costs or outlay of the investment to obtain the technology.
Cost reduction (C_{12})	The reduction in yearly operation costs or expenditures as a result of using the technology.
Revenue increase (C_{13})	The increase in revenue (through an increase in yield or quality) as a result of using the technology.
Environmental impacts (C_2)	The ability of the technology to reduce negative environmental impacts (greenhouse gas/carbon emissions and chemical residues) generated from the greenhouse production process.
Trialability (C_3)	The ease with which the technology can be tested and tried on a small scale in the greenhouse before having to decide to adopt it.
Observability (C_4)	The benefits or results of using the technology are tangible, have social visibility, they can be observed, imagined, and perceived by myself and others.
Complexity (C_5)	The level of difficulty to understand, learn, and use the technology.
Compatibility (C_6)	How well the technology fits well the existing greenhouse physical infrastructure and the established work routine, practices, and management platform.

The evaluated technologies are sap flow sensor, leaf temperature sensor, deleafing robot, harvesting robot, and scouting robot. A description of the functionalities of the technologies is given in Table 5.2. As these technologies are still at the trail stage and there is little knowledge and commercial application of these technologies, experts were consulted on their performance.

Table 5.2. Description of the evaluated greenhouse technologies.

Technology	Function
Sap flow sensor (T_1)	Monitoring plant water consumption, which can reflect water deficit or over-irrigation of plant status.
Leaf temperature sensor (T_2)	Providing real-time data on the surface temperature of plant leaves to avoid overheating or unwanted cooling.
Deleafing robot (T_3)	Detecting leaf petioles and cutting the old leaves.
Harvesting robot (T_4)	Localizing and determining the ripeness of fruit; griping and detaching ripe fruit and transport of a detached fruit.
Scouting robot (T_5)	Detecting pests and diseases, mapping defects caused by pests, and counting flowers and fruits.

5.2.1 Bayesian BWM

Best-worst method (BWM) is a multi-criteria decision-making (MCDM) method developed by Rezaei (2015) for a complex problem with multiple conflicting and subjective criteria. BWM makes use of pairwise comparisons for weighting. In the BWM, $2n - 3$ comparisons are evaluated by the decision-maker for a problem with n criteria. According to Rezaei (2020), BMW offers advantages over other MCDM methods in establishing a clear understanding of the range of evaluation for the decision-maker, mitigating possible anchoring bias, and thus generating more consistent pairwise comparisons. The procedure of BWM can be summarized in five steps:

Step 1. Determine a set of decision criteria $C = \{c_1, c_2, \dots, c_n\}$.

Step 2. Identify the best (most important) c_B and the worst (least important) criteria c_W.

Step 3. Determine the preference of the best criterion B over all the other criteria using a number between 1 and 9 (1: equally important, 9: extremely more important). The resulting Best-to-Others vector would be:

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$$

where a_{Bj} indicates the preference of the best criterion B over criterion j, with $a_{BB} = 1$.

Step 4. Determine the preference of all the other criteria over the worst criterion W using a number between 1 and 9. This results in the Other-to-Worst vector

$$A_W = (a_{1W}, a_{2W}, \dots, a_{nW})^T$$

where a_{jw} indicates the preference of criterion j over the worst criterion W, with $a_{WW} = 1$.

Step 5. Calculate the optimal weights $(w_1^*, w_2^*, \dots, w_n^*)$. The optimal weights are derived by solving the following problem:

$$min\ \xi$$

$$\text{s.t.} \sum_j w_j = 1$$

$$\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \xi, \text{ for all } j$$

$$\left|\frac{w_j}{w_W} - a_{jW}\right| \leq \xi, \text{ for all } j$$

Solving the above problem gives the optimal weights $(w_1^*, w_2^*, \dots, w_n^*)$ and ξ^*.

The consistency of the decision-maker's judgement is evaluated by the consistency ratio $=$ $\xi^*/$consistency index. The value of the consistency index depends on the value of a_{BW} (Table 5.3). The lower the consistency ratio, the higher the reliability of the result. In case of inconsistency, a DM is asked if they are willing to reconsider the judgement for the most inconsistent pair-wise comparison.

Table 5.3. Consistency index (CI) table, from Rezaei (2015).

a_{BW}	1	2	3	4	5	6	7	8	9
CI	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

BWM can calculate a weight vector for one DM at a time. When multiple DMs are present, a single weight vector for the group is often obtained by aggregating individual priorities using, for example, the arithmetic or geometric mean (Ishizaka & Labib, 2011). However, this way of aggregation is sensitive to outliers. If one DM has different weights from the entire group, the aggregated group weights will be significantly influenced. Moreover, the information on the dispersion of DM's preference is also lost due to the aggregation (Mohammadi & Rezaei, 2020). In group MCDM problems, a criterion is ranked as more important than another merely if its group (weighted) average weight is higher than another. However, this way of determining the ranking of criteria does not reveal the confidence of the importance relationship between each pair of criteria.

The nature of the underlying problem is a group decision-making problem. Facing the preferences of a group of DMs, we want to develop a deeper understanding of the confidence of importance of criteria among stakeholders. In 2019, Mohammadi & Rezaei (2020) proposed the Bayesian Best-Worst method (Bayesian BWM). The inputs of the Bayesian BWM are the same as those of the original BWM. The difference is that the Bayesian BWM assumes the optimal group weights as a probability distribution, rather than a precise weight vector. The notion of credal ranking was introduced to describe the degree to which one criterion is more important than one another.

The Bayesian BWM meaningfully views the multicriteria group DM problem from a probabilistic perspective. The criteria are seen as random events, and the weights are their likelihoods of occurrence. For probabilistic reasoning, all the inputs and outputs of the Bayesian BWM are modeled as probability distributions. The inputs of the BWM, the Best-to-Others vector A_B^k and the Others-to-Worst vector A_W^k, are modeled as multinomial distributions:

$$A_W^k|w^k \sim multinomial(w^k), \qquad \forall k = 1, \dots, K$$

$$A_B^k|w^k \sim multinomial\left(\frac{1}{w^k}\right), \qquad \forall k = 1, \dots, K$$

The weight vector w is modeled as the Dirichlet distribution, which satisfies the non-negativity and sum-to-one properties. The Dirichlet distribution is a conjugate prior of the multinomial distribution, which means that the posterior distribution would also be a Dirichlet distribution:

$$Dir(w^{agg}|\alpha) = \frac{1}{B(\alpha)}\prod_{j=1}^{n} w_j^{\alpha_j - 1}, \qquad \alpha \in \mathbb{R}^n$$

The individual weight vector w^k is expected to be in the proximity of w^{agg}:

$$w^k|w^{agg} \sim Dir(\gamma \times w^{agg}), \qquad \forall k = 1, \dots, K$$

where γ is a non-negative parameter that governs the closeness between w^k and w^{agg}. γ follows a gamma distribution:

$$\gamma \sim gamma(a, b)$$

The values of a and b were set to 0.1, as $gamma(0.1, 0.1)$ is similar to a uniform distribution. Using it as an uninformative prior distribution can avoid biased inference on the posterior distribution.

A Bayesian hierarchical model is proposed to compute the overall weights of the group DM problem (see Figure 5.2). The value of the overall group weight vector w^{agg} depends on the weight of individual DM w^k; the value of w^k is dependent on A_B^k and A_W^k.

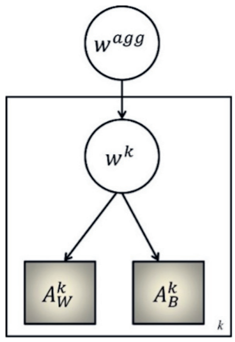

Figure 5.2. Probabilistic hierarchical model of the Bayesian BWM, from Mohammadi & Rezaei (2020).

The prior distribution of w^{agg} is modeled as an uninformative Dirichlet distribution:

$$w^{agg} \sim Dir(1)$$

The specified Bayesian model does not have a closed-form solution. The posterior distributions can be computed using the Markov-chain Monte Carlo (MCMC) technique (Gilks et al., 1995). The "just another Gibbs sampler" is used to generate the random sample (Plummer, 2004). The confidence of the importance relations between various criteria (credal ranking) can be calculated based on the approximated posterior distribution of w^{agg}. For details on the Bayesian BWM, please refer to the work of Mohammadi & Rezaei (2020). For this study, we used a Bayesian BWM solver (https://bestworstmethod.com/software/) to compute the weight vector of stakeholders and the experts' scores of technologies performance.

5.2.2 Data collection on stakeholders' preferences

We collected data from four groups of stakeholders: greenhouse growers, private investors, machinery and equipment suppliers, and agricultural policy makers in China. The interviewees were asked to provide their functions to verify their eligibility to be qualified respondents. Growers were only included if they are in cultivation management roles, e.g., setting greenhouse climate strategies, and managing labour, in a modern greenhouse. Investors were general managers or directors in a modern greenhouse company, located in Beijing, Shanghai, Shandong, Gansu, Jiangsu, Yunnan, and Guangdong provinces. The sample of growers and investors covers the stakeholders of major modern greenhouse companies in China. Machinery and equipment suppliers were the technical or marketing specialists from companies that provide equipment, such as sensors, climate computers, and screens, to greenhouse companies. Policy makers were recruited from the local ministry of agriculture, agricultural research institutes, extension centers, and quasi-commercialized state-owned enterprises. Policy makers were only included if they had participated in the design of local agricultural policy or had been involved in local greenhouse projects. 10 respondents for each group were reached through snowball sampling.

Additional information on age, management experience (in years), greenhouse size, types of crops planted, and educational level were collected from growers. In the sample of growers, almost everyone grows tomatoes. Half of them also planted cucumbers. A few grow flowers, peppers, or lettuce. Only one grower cultivates hops for beer brewing. The grower ranges from 30 to 48 years old, with an average age of 36 years. They have been working in the greenhouse sector for 5 to 13 years, managing a greenhouse of 5 to 30 hectares. Most of them hold a bachelor's degree or higher.

The survey was designed according to the guidelines of BWM (see supplementary material) and documented in Excel format. The surveys were conducted through a web conferencing platform and presented to the respondents through screen sharing. At the beginning of the survey, a list of greenhouse plant-monitoring sensors and automation technologies and their functions was presented. Each interviewee was asked if they had heard of or worked with these technologies. Next, an overview of all evaluation criteria was presented, during which the interviewer read out the description of each criterion in Table 1 for the respondent. In the main part of the survey, respondents were asked to indicate which criteria would be the most and least important in a situation where they use (for growers)/ adopt (for investors)/ promote (for policy makers)/ communicate (for suppliers) a digital or automation technology for greenhouse production. Respondents were then asked to compare the other criteria to the selected most and least important criteria, by assigning a number between 1 and 9. The respondents were asked to explain the choices they made throughout the interview. A BWM solver was employed to calculate the optimal weights and consistency ratio. The interview ended with some general discussion, where the respondents were invited to share their experiences on using, adopting, communicating, or promoting greenhouse technologies. Each interview lasted 40 to 70 minutes.

5.2.3 Expert evaluation of technology performance

A second round of interviews was conducted with the technical experts to elicit the score of technologies on a given criteria. The experts were selected to make sure they have knowledge about each technology. Experts from both the academic and the industry were included to make sure that the expertise was complementary. Table 5.4 shows the background and expertise of the experts. An example of the questionnaire with experts can be found in supplementary material.

Table 5.4. Experts' details.

Expert	Background
#1	Industry. Director of a horticultural consultancy company.
#2	Academia. Senior Scientist, Wageningen University& Research. Experts on crop production, crop physiology, cropping systems, and crop growth models.
#3	Industry. Director of an agricultural robotic company.
#4	Academia. Senior Scientist, Wageningen University& Research. Experts on sensors and detection systems.

5.2.1 Overall performance of technology

A composite index, the overall technology performance score (S^t), was developed by combining stakeholder preferences and expert scores:

$$S^t = w_1(w_{11}s_{11}^t + w_{12}s_{12}^t + w_{11}s_{13}^t) + \sum_{i=2}^{6} w_i s_i^t$$

where w_{11}, w_{12}, and w_{13} are the weights of the *cost-benefit* sub-criteria. s_{11}^t, s_{12}^t, and s_{13}^t are the expert scores of technology t on the three sub-criteria of *cost-benefit*. w_i and s_i^t are the stakeholder weight of and the expert score of technology t on criterion i.

Stakeholder preferences and expert scores were both estimated using the Bayesian BWM. The MCMC sampled 15,000 weight vectors from the posterior distributions of $(w_1, \ldots, w_6)$ and (w_{11}, w_{12}, w_{13}), and 15,000 score vectors from the posterior distribution of $(s_i^1, \ldots, s_i^5)$. Multiplying the weight vectors and the score vectors based on the formula above produces an approximation of the probability distribution of the overall performance scores of technologies. The credal ranking of the overall performance scores of technologies could be calculated based on the 15,000 samples of the overall performance score.

5.3 Results

5.3.1 Stakeholders' heterogeneous preferences on technology attributes

The overall optimal global weights of the six attributes and the local weights of the *cost-benefit* sub-criteria of each stakeholder group are shown in Table 5.5 and 5.6. *Cost-benefit* was the most important criterion for all stakeholder groups. Furthermore, different stakeholders showed different preferences for the technology attributes defined in the DOI.

Table 5.5. The overall optimal global weights and their rankings of different stakeholder groups.

Criteria	Growers	Investors	Suppliers	Policy makers
C_1 Cost-benefit	0.308 (1)	0.314 (1)	0.319 (1)	0.292 (1)
C_2 Environment	0.108 (5)	0.110 (6)	0.110 (6)	0.155 (4)
C_3 Trialability	0.176 (2)	0.128 (4)	0.112 (5)	0.124 (5)
C_4 Observability	0.136 (4)	0.201 (2)	0.180 (2)	0.160 (2)
C_5 Complexity	0.099 (6)	0.129 (3)	0.131 (4)	0.109 (6)
C_6 Compatibility	0.174 (3)	0.119 (5)	0.148 (3)	0.160 (2)

Note: Rankings are shown in parentheses.

Table 5.6. The overall optimal local weights of the *cost-benefit* sub-criteria of different stakeholder groups.

Criteria	Growers	Investors	Suppliers	Policy makers
C_{11} Initial investment	0.230	0.213	0.258	0.329
C_{12} Cost reduction	0.396	0.267	0.482	0.218
C_{13} Revenue increase	0.375	0.520	0.260	0.415

Policy makers ranked *environmental impact* as the fourth most important criterion. The group weight on *environmental impact* of policy makers was 0.155, while that of growers, investors, and suppliers was 0.108, 0.110, and 0.110, respectively. According to policy makers, there are existing environmental regulations in place for greenhouse production. For example, the local agricultural bureau does not approve greenhouse projects that use coal for heating or do not recycle drain water. However, these assessments are typically performed at the initial stages of greenhouse projects. *Environmental impact* was the least or the second least important criterion for growers, investors, and suppliers. One investor stated, "If the additional costs of environmentally friendly technologies are not compensated by other entities, *environmental impacts* would be my least concern." Nevertheless, some investors have recognised that *environmental impact* may become increasingly important in the future. Two investors mentioned that they have started greenhouse gas emission accounting for their greenhouse production, in anticipation of the possible extension of the cap-and-trade system, currently limited to the power generation sector, to the agricultural sector in China.

Trialability was ranked as the second most important criterion among growers, while it was ranked the fourth or fifth for other stakeholders. This can be attributed to the fact that *trialability* is directly related to the implementation of technology, making it more relevant for growers, who are the end-users of technologies. During interviews, several investors indicated that they would only adopt technologies that have demonstrated benefits. In China, the government often takes the lead in introducing new agricultural technologies, typically through demonstration programs. Once there are sufficient successful use cases for a technology, the investors would not bother to conduct trials in their greenhouses before adopting it. One supplier also confirmed that many large-scale greenhouses in China do not typically conduct trials.

Observability was ranked second in importance for investors, suppliers, and policy makers, while it is of lesser importance (fourth) for growers. Growers indicated that their primary focus is yield and quality, and whether the technology has high observability is not a key concern for them. One investor raised the point that evaluating the benefit of a technology can be challenging if its effects are not easily observable for them as investors, who do not have specialised knowledge on agricultural production. One policy maker mentioned that *observability* is a primary factor to consider for the government when promoting innovative technologies.

Complexity was the least important criterion for growers, a finding that differs from many previous studies on agricultural technology adoption (e.g., Aubert et al., 2012; da Silveira et al., 2023; Reichardt et al., 2009). This finding can be attributed to the unique sample of growers in our study, who work as managers in high-tech greenhouses, and most of whom have a bachelor's degree or higher. Several growers stated that learning new technologies is part of their job and that being able to master complex technologies is a demonstration of their professional competence. *Complexity* is also the least of policy makers' concerns. According to one policy maker, modern farmers possess greater skills than farmers of the past, and when promoting greenhouse technologies, the government aims to support skilled farmers who can act as early adopters and knowledge disseminators within the farmer network. Among investors, *complexity* was ranked third in importance. One investor suggested that a complicated technology might incur indirect costs associated with employee training. Another investor expressed concerns about the sunk cost of the initial investment if employees were unable to master a complicated technology.

Compatibility was one of the primary concerns for growers, suppliers, and policy makers, but was only ranked fifth among investors. Investors tended to believe that incompatibility issues can be easily solved. If the technology is incompatible with employees' working routines, the problem can be addressed by establishing standard operating procedures for employees. Modifying the physical infrastructure is not a problem either, as the adjustment only needs to be made once, as long as the adjustment costs can be offset by the economic benefits of the technology. One supplier suggested that the importance of *compatibility* depends on the nature of the technology. For automation technologies, *compatibility* is not a major concern, but it is critical for sensors that deal with data. One grower confirmed that growers prefer to operate on one integrated data platform that has access to all sensor data. Furthermore, a policy maker suggested that when they are promoting greenhouse technologies, they do not only focus on technologies that can be applied in high-tech greenhouses, but also consider the potential of a technology to be spread to solar or plastic greenhouses, which accounts for over 90% of the protected horticultural area in China.

5.3.2 Performance scores of technologies on the given attribute

Table 5.7. Performance scores and their rankings of technologies on the given criteria.

Criteria	**Sap flow sensor**	**Leaf temperature sensor**	**Deleafing robot**	**Harvesting robot**	**Scouting robot**
C_{11} Initial investment	0.370 (2)	0.389 (1)	0.083 (4)	0.067 (5)	0.091 (3)
C_{12} Cost reduction	0.082 (4)	0.080 (5)	0.274 (2)	0.389 (1)	0.176 (3)
C_{13} Revenue increase	0.207 (2)	0.195 (3)	0.160 (5)	0.169 (4)	0.269 (1)
C_2 Environment	0.166 (3)	0.198 (2)	0.125 (4)	0.108 (5)	0.403 (1)
C_3 Trialability	0.339 (2)	0.371 (1)	0.087 (4)	0.071 (5)	0.131 (3)
C_4 Observability	0.071 (5)	0.094 (4)	0.244 (2)	0.360 (1)	0.231 (3)
C_5 Complexity	0.090 (5)	0.111 (4)	0.310 (1)	0.277 (2)	0.213 (3)
C_6 Compatibility	0.313 (2)	0.361 (1)	0.102 (2)	0.073 (5)	0.151 (3)

Note: Rankings are shown in parentheses.

Table 5.7 presents the score on each attribute of each technology. The leaf temperature sensor has the lowest *initial investment costs*, with one leaf temperature sensor costing less than 1000 euros. The investment costs for sap flow and leaf temperature sensors are similar. Compared to sensors, robotic technologies are much more expensive. The initial investment costs of harvesting robots are higher than deleafing robots, and the initial investment of deleafing robots is higher than scouting robotics. According to experts, one harvesting robot costs between 80,000 and 150,000 euros. Experts predicted a significant reduction in the cost of robotics in the future. They also anticipate that the business model of sensor and robotics producers will differ greatly. Robotics are more likely to be adopted based on a leasing model, where greenhouse firms do not need to purchase ownership of the robotics, but instead can lease them from agricultural equipment service providers.

Labour costs typically make up a sizeable portion of the operating costs, and automation technologies are aimed at replacing human labour. Among the robotic technologies, the harvesting robot has the greatest potential for decreasing operating costs, followed by the deleafing robot and scouting robot. This is because the labour requirements for harvesting are higher compared to deleafing and scouting. Sensors have limited capacity to reduce the operating costs of greenhouse production.

All five technologies have the potential to *increase the revenue* of greenhouse production. The scouting robot can prevent production loss by detecting pests and diseases at an early stage, therefore increasing revenue. The sap flow sensor can provide better insights into crop development, possibly leading to higher yield and crop quality and thus higher revenue.

All experts rated the scouting robot as the most *environmentally friendly* technology because of its ability to detect and prevent pests and diseases, leading to a reduction in chemical use. The deleafing robot could enhance environmental performance by performing more precise cutting than human labour, reducing the likelihood of diseases caused by inaccurate cutting and consequently reducing chemical use. The leaf temperature sensor has the potential to reduce greenhouse gas emissions generated from energy use, provided that growers can improve temperature management based on sensor data.

Sensor technologies in general scored higher than robotics in terms of *trialability*. The installation of sap flow and leaf temperature sensors is relatively easy, by clipping them to the plant or positioning them above the canopy. Once upon installation, they simply generate data without affecting operations in the greenhouse. To a robot, especially the deleafing and harvesting robot, growers need to conduct multiple trials, row by row to evaluate its performance in their greenhouses. Among the robotic technologies, the scouting robot is the easiest to trial as it does not perform any actions on stems or fruits, making it less risky to trial. The harvesting robot received the lowest score for trialability. This is because if the harvesting robot fails to identify the correct cutting position, it risks damaging the main stem, which will result in the production loss of the entire stem.

Robotic technologies generally scored higher than sensors on *observability*. The harvesting robot scored the highest on observability. The concept of the harvesting robot can be understood even by those who are not familiar with greenhouse production, whereas it is not the case for the deleafing robot. Sensors are much smaller in size and therefore less visible compared to robotics.

According to experts, sensors generally scored lower on *complexity* than robotic technologies. Following the taxonomy of previous studies on precision agriculture, robotics falls into the category of embodied knowledge technologies, while sensors are information-intensive technologies (Miller et al., 2019). For robotics, the value of the technology is 'embodied' within it, and it does not require specialized skills for end-users to make full use of the technology. However, for sensors, while they are easy to install, experts tend to believe that it is difficult for growers to translate the data generated by sap flow sensors into meaningful managerial decisions. Growers need to have good knowledge of plant physiology to fully leverage the data generated by sap flow and leaf temperature sensors.

Robotic technologies are less *compatible* than sensor technologies because they require more modifications to the physical infrastructure of the greenhouse, such as the pipe-rail system or the power station. In contrast, sensors can be easily installed with little or no change to the greenhouse infrastructure. The harvesting robot received the lowest score for compatibility. To successfully integrate the harvesting robot, it requires additional modifications to the logistics system to enable the automatic grading and packing of fruit directly after harvesting. The scouting robot needs a computer connection to track its movements and record data on pests and diseases.

5.3.3 Overall scores and credal rankings of technologies

Table 5.8 displays the calculated overall performance scores and rankings, using the weights of the different stakeholder groups. In terms of the two sensor technologies, the leaf temperature sensor scored higher than the sap flow sensor across all stakeholder groups. The deleafing robot received the lowest overall performance score using the weights of all stakeholder groups. The harvesting robot received the highest score using the weight of suppliers, while the scouting robot obtained the highest score according to the weights given by investors.

The credal rankings of the overall performance scores of the technologies for each stakeholder group are shown in Figure 5.3 to 5.6. The interrelation of the between technology performance is represented by direction and weight. From the grower's perspective, the leaf temperature sensor and sap flow sensor were ranked first and second, respectively, among all technologies. The scouting robot was ranked third in terms of the overall performance score; however, the confidence of the sap flow sensor has a higher overall score than the scouting robot is only 0.57. The harvesting robot was ranked fourth on the overall performance score for growers.

Table 5.8. The overall performance scores and rankings of technologies of different stakeholder groups.

Technology	**Grower**	**Investor**	**Supplier**	**Policy maker**
Sap flow sensor	0.210 (2)	0.190 (4)	0.187 (4)	0.208 (3)
Leaf temperature sensor	0.233 (1)	0.210 (2)	0.209 (3)	0.231 (1)
Deleafing robot	0.168 (5)	0.181 (5)	0.185 (5)	0.166 (5)
Harvesting robot	0.184 (4)	0.202 (3)	0.211 (1)	0.180 (4)
Scouting robot	0.204 (3)	0.218 (1)	0.208 (3)	0.216 (2)

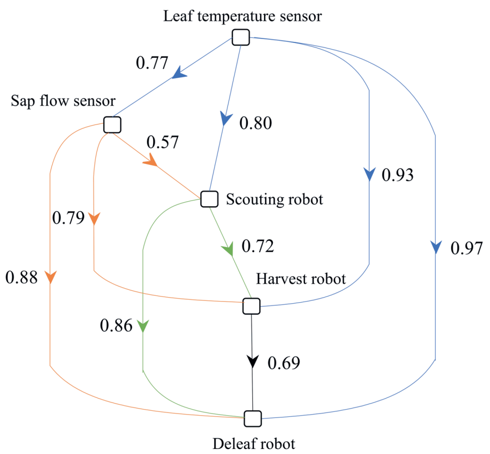

Figure 5.3. Credal ranking on the overall performance of technologies – growers' perspective.

For investors, the scouting robot has the highest overall performance score, followed by the leaf temperature sensor. The confidence of the scouting robot has a higher overall score than the leaf temperature sensor is only 0.58; and the confidence of it has a higher overall score than the harvesting robot, the third-ranked technology, is 0.65. According to the overall performance score, the sap flow sensor is less interesting to investors compared to the scouting robot, leaf temperature robot, and harvesting robot.

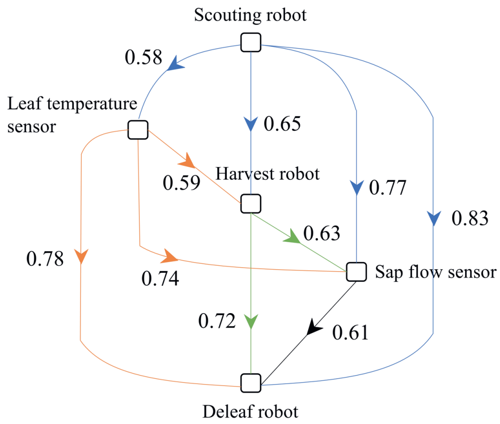

Figure 5.4. Credal ranking on the overall performance of technologies – investors' perspective.

For suppliers, the harvesting robot, leaf temperature sensor, and scouting robot are the technologies with the three highest overall performance scores, and their scores are similar. The confidence between each pair of these three technologies is just above the 0.5 threshold. The sap flow and deleafing robot were the technologies with the lowest scores, and their scores were also similar.

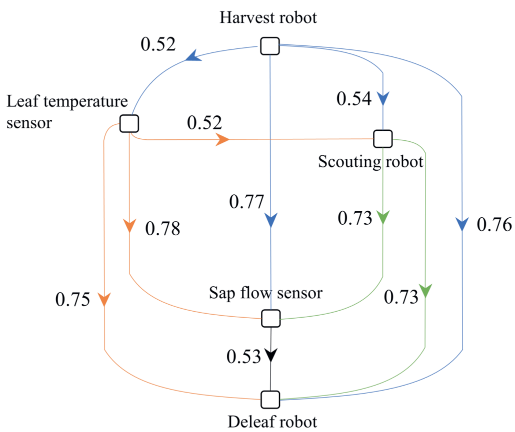

Figure 5.5. Credal ranking on the overall performance of technologies – suppliers' perspective.

The leaf temperature sensor received the highest score calculated using the preferences of policy makers, followed by the scouting robot and sap flow sensor. The harvesting robot, which was ranked first among suppliers, was ranked only fourth among policy makers. The deleafing robot was ranked last in terms of the overall performance score for all stakeholder groups.

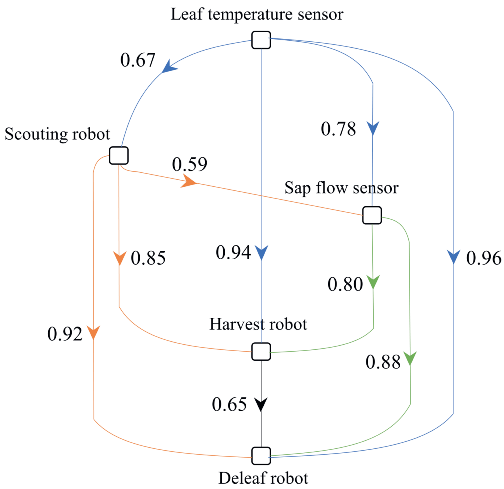

Figure 5.6. Credal ranking on the overall performance of technologies – policy makers' perspective

5.4 Conclusions and discussion

This study examined the heterogeneous preferences of different stakeholders regarding the adoption of innovative greenhouse technologies in China. Group weights for the six perceived attributes of the technologies were elicited using the Bayesian BWM. In addition, five innovative greenhouse technologies were evaluated by experts on the defined attributes using the same method. An overall performance score was developed to gain insight into the adoption and diffusion potential of these technologies.

To our knowledge, this is the first study to provide a comprehensive evaluation of sensor and robotic technologies in a commercial greenhouse production setting. It contributes to bridging the gap between technology assessment and adoption by adopting an innovation-oriented perspective. This approach emphasizes the factors that are crucial to successful technology diffusion, rather than limiting the evaluation to a narrow techno-centric view. By involving not only experts but also stakeholders involved in the technology adoption and diffusion process, the evaluation process aims to yield more robust results and incorporate richer perspectives compared to evaluations conducted solely by experts (Grunwald, 2009).

This study contributes to the technology assessment literature by introducing a probabilistic evaluation score through the application of the Bayesian BWM. By combining stakeholder preferences and expert scores, both modeled as Dirichlet distributions, probability distributions of the overall performance scores of different technologies were obtained. This approach allows for a probabilistic ranking of technologies based on distributions, rather than relying solely on the absolute value of the scores. It offers a more nuanced understanding of the confidence relationship between technology performance. This approach is particularly suitable for early-stage assessment of technologies with limited information available.

The findings offer insights to policy makers on designing effective policies to facilitate the ongoing digital transformation of the greenhouse sector in China. The heterogeneous preferences of stakeholders and technology performance underscore the need to tailor strategies for disseminating innovative technologies to accommodate the specific priorities of each stakeholder group. For example, to convince growers, the focus should be on showcasing the compatibility and trialability of technologies. This can be achieved through demonstration programs organized by policy makers and technology suppliers.

The findings on technology performance also hold relevance for other countries, as the available technologies and production environments in high-tech greenhouses are similar across countries. The high initial investment costs and limited trialability pose potential barriers to the adoption of robotic technologies. Technology developers should note the low ranking of the deleafing robot among all stakeholder groups, indicating the possible low acceptance in the future. To promote sensor technologies, which score low on *observability*, efforts should be made by extensionists and technology suppliers to provide growers and investors with access to information about these technologies. It is worth noting that although the leaf temperature sensor received high overall performance scores, its low *complexity* score suggests the possibility of disadoption after initial adoption. To ensure the continued adoption of sensors, comprehensive training programs should be offered by expansionists and technology suppliers to empower growers with knowledge and skills to fully leverage the values of sensor technologies.

It is important to acknowledge that this study, like any quantitative study, has some inherent limitations. The results of the evaluation are highly dependent on the criteria included in the evaluation framework. In this study, the evaluation criteria are based on the DOI theory, which is widely used in agricultural innovation studies. However, it is important to recognize that the DOI theory cannot capture all the complexities of agricultural technologies. Lyytinen and Damsgaard (2001) criticized the completeness of the technology attribute list defined by the DOI and questioned whether all innovations can be adequately characterized using these attributes. It is worthwhile to consider additional criteria such as data safety (Shang et al., 2021), user safety (Hemming, 2020), social impact (Schimmelpfennig, 2016), which have been used in other studies focusing on digital technologies.

The results of the assessment should not be seen as a replacement for decision-making, but rather as information to support the decision-making process. One challenge of technology assessment is the integration of multiple evaluation criteria, as highlighted by Grunwald (2009). Technology alternatives were often assessed based on various criteria, some of which are partially incommensurable. To achieve a comprehensive evaluation, these criteria need to be carefully weighted and aggregated. The *overall performance score* is a highly aggregated construct, calculated as the sum of weights multiplied by scores, which convert performance on disparate criteria to a common scale. The calculations are highly dependent on the specific weighting and aggregation procedure used, and the resulting weights are subjective to the assumptions and subjective scaling procedures of the Bayesian BWM, which also determines how the quantitative results should be interpreted appropriately.

Furthermore, this study is a “static” assessment and does not account for the dynamic nature of technological progress that may occur in the future. The technologies were evaluated based on their current cost and capabilities. However, sensor and robotic technologies evolve rapidly. For example, experts predict significant improvements in the speed and cost reduction of harvesting robots in the future. Additionally, the study evaluates technologies independently, without considering potential interdependencies between technologies. For example, an expert indicated that effective leave pruning is a prerequisite for the successful operation of harvesting robots. Future research could incorporate the dynamics of technological progress and consider technology bundles in their assessment.

Nevertheless, these limitations do not diminish the value of this research. This study was based on a transparent evaluation procedure. By considering multiple criteria and taking into account the complex networks of stakeholders involved, this study provides valuable insights for technology assessment and offers a systematic and structured framework for evaluating technologies.

CRediT authorship contribution statement

Xinyuan Min: Conceptualization, Methodology, Interview, Data curation, Formal analysis, Writing - Original Draft. **Jaap Sok**: Conceptualization, Methodology, Supervision, Writing - review & editing. **Tian Qian**: Funding acquisition, Interview. **Weihao Zhou**: Interview, Data curation. **Alfons Oude Lansink**: Funding acquisition, Methodology, Supervision, Writing - review & editing.

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Competing interests statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Chapter 6 General discussion

6.1 Introduction

The overall objective of this dissertation was to assess the economic feasibility of greenhouse investments and to identify greenhouse designs, as well as sensor and robotic technologies, that align with the preferences of multiple stakeholders. The ultimate goal was to contribute to well-informed decision-making on investment and policy design in China's greenhouse sector. More specifically, this thesis (1) developed a bio-economic model that assesses the economic feasibility of greenhouse production, taking into account input and output price uncertainty, (2) developed an optimization framework that identifies greenhouse designs that are optimally adapted to regional climatic and market conditions, considering the varying priorities of investors and policy makers for economic and environmental performance, (3) examined the impact of uncertainty in output price and the abolition of subsidy policies on the timing of investment in high-tech greenhouses, and (4) analysed the preferences of different stakeholder groups in China's greenhouse sector for sensor and robotic technologies.

This concluding chapter begins with a synthesis of the results. The implications of the thesis for business and policy makers are discussed in section 6.3. Section 6.4 reflects on the data and methods used in this thesis, followed by recommendations for future research. This chapter ends with the main conclusions of this dissertation.

6.2 Synthesis of the results

6.2.1 Greenhouse investment under uncertainty

Greenhouse investments are subject to many types of uncertainty. This paper has focused mainly on price and policy uncertainty, and this section discusses how price and policy uncertainty affect economic feasibility, optimal greenhouse designs, and the timing of greenhouse investments.

Chapter 2 developed a bio-economic model that assesses the economic feasibility of greenhouse investment for tomato production. The model incorporated uncertainty in both input and output prices and generated the probability distributions of the Net Present Value (NPV) of investing in a greenhouse for tomato production for four locations in China using Monte Carlo simulation. The wide range of NPVs suggests that fluctuations in tomato and natural gas prices can significantly affect the economic feasibility of greenhouse investments, making their economic returns highly uncertain.

Specifically, in Jinshan, NPVs ranged from −829.4 ¥ m^{-2} at the 5th percentile to −355.5 ¥ m^{-2} at the 95th percentile, with a mean of −593.7 ¥ m^{-2}. In Langfang, the range was from −301.2 ¥ m^{-2} at the 5th percentile to 347.8 ¥ m^{-2} at the 95th percentile, with a mean of 29.4 ¥ m^{-2}. In Weifang, the NPVs ranged from −1231.0 ¥ m^{-2} at the 5th percentile to −705.8 ¥ m^{-2} at the 95th percentile, with a mean of −957.8 ¥ m^{-2}. In Pingliang, the range was from 182.0 ¥ m^{-2} at the 5th percentile to 749.3 ¥ m^{-2} at the 95th percentile, with a mean of 477 ¥ m^{-2}. The analysis in Chapter 2 differs from previous studies that used deterministic prices for the economic evaluation of greenhouses (Naseer et al., 2021; Vanthoor et al., 2012; Xue, 2017).

Price uncertainty also affects the choice of greenhouse design. While a greenhouse design may be considered optimal under a given set of prices, it may not remain optimal under different price scenarios. Chapter 3 identified the optimal greenhouse designs under three different price scenarios: the baseline scenario, the low tomato price scenario, and the high energy price scenario. The identified designs varied depending on the specific price scenario, highlighting the importance to consider price uncertainty when selecting greenhouse designs. This aspect has been largely overlooked in existing greenhouse design literature (e.g., Ghoulem et al., 2019; Golzar et al., 2021; Naseer et al., 2021; Vanthoor et al., 2012).

Compared to price uncertainty, there is a relative dearth of studies addressing policy uncertainty in agricultural systems (Komarek et al., 2020). The scenario analysis in Chapter 2 compared two scenarios: one without subsidy and another with a fixed subsidy level of 50% on the initial investment. However, subsidy policies can change over time. It is likely that the current subsidy scheme may be phased out in the future, introducing further uncertainty into greenhouse investment.

Building upon the bio-economic model developed in Chapter 2, Chapter 4 examined the role of policy uncertainty in greenhouse investment decisions. Using a real options framework that simultaneously accounts both price and policy uncertainty, this chapter found that uncertainty about the phasing-out of the subsidy scheme significantly reduces the value of waiting and induces earlier investment. Moreover, an increase in the subsidy level could also reduce the value of waiting and encourage earlier investment, even without the risk of the subsidy being terminated. The combination of a high subsidy level and the signalling of subsidy termination could greatly reduce the value of waiting and prompt immediate investment. Contrary to earlier studies that concluded policy uncertainty generally leads to delayed investment (Floridi et al., 2013; Purvis et al., 1995), our findings suggest that it can also induce earlier investment, a conclusion that aligns with Yanore et al. (2023a).

6.2.2 Optimal greenhouse designs and technology evaluation

The complexity of agricultural systems requires the engagement and coordination of multiple stakeholders (Kilelu et al., 2013; UNEP et al., 2023). In light of this, Chapters 3 and 5 adopted a multi-stakeholder approach. This section discusses how stakeholder preferences affect optimal greenhouse designs and evaluation of emerging technologies.

Chapter 5 evaluated five sensor and robotic technologies for greenhouse operations, using the technology attributes defined in the Diffusion of Innovation theory. Four key stakeholder groups were identified: growers, investors, technology suppliers and policy makers. The elicitation of preferences revealed notable differences among these groups.

For all stakeholder groups, the cost-benefit of technology was the most important attribute. Observability was the second most important attribute for investors, technology suppliers, and policy makers. Despite its importance, it has received less attention in the agricultural innovation literature compared to other attributes such as compatibility and complexity (Kante et al., 2017; Pathak et al., 2019). This underscores the potential need for more attention to this attribute in agricultural innovation studies. Compatibility of technology was the third most important attribute among growers, suppliers, and policy makers. The importance of compatibility on the adoption of agricultural innovation was supported by other studies (Aubert et al., 2012; Kante et al., 2017). Interestingly, growers ranked complexity of technology as the least important attribute, a finding that differs from previous research (Aubert et al., 2012; Reichardt & Jürgens, 2009; Robertson et al., 2012). This discrepancy is likely due to our unique sample: growers who predominantly hold a bachelor's degree or higher and work as managers in high-tech greenhouses. Policy makers are more concerned about the environmental impact of technology, ranked it fourth. In contrast, it was the least important among investors and technology suppliers.

By combining stakeholder preferences with expert-rated technology scores for each attribute, an overall performance score was obtained for each technology. The deleafing robot obtained the lowest score across all stakeholder groups. The harvesting robot received the highest score when evaluated by suppliers' preferences, while the scouting robot received the highest score based on the weights of investors. For the two sensor technologies, the leaf temperature sensor consistently scored higher than the sap flow sensor across all stakeholder groups. These divergent outcomes clearly demonstrate that incorporating stakeholder preferences in technology assessment would result in different rankings of technology for different stakeholder groups.

Stakeholder preferences were also taken into account in the selection of greenhouse designs in Chapter 3. According to Chapter 5, policy makers place greater emphasis on environmental impact than investors. Their varying priorities need to be considered when determining optimal greenhouse designs. To address this, Chapter 3 employed a directional distance function to assess the overall performance of greenhouse designs. Specifically, the relative importance of the economic and environmental dimensions of investors and policy makers, as elicited in Chapter 5, was incorporated into the directional distance function via the directional vector. By incorporating stakeholder preferences and addressing several objectives, this study distinguishes itself from previous greenhouse design optimization studies (e.g., Ghoulem et al., 2019; Golzar et al., 2021; Naseer et al., 2021; Vanthoor et al., 2012), which typically focus on a single objective within a single stakeholder perspective.

Chapter 3 identified a set of efficient greenhouse designs that are optimal for both investors and policy makers. Here, an "efficient design" was defined as one where neither an increase in revenue nor a reduction in greenhouse gas (GHG) emissions can be achieved without incurring additional fixed or operating costs. Notably, the identified optimal greenhouse designs differ from one region to another. This highlights the importance of adopting the "adaptive greenhouse" concept (Van Henten et al., 2006), which advocates for tailoring greenhouse designs to the specific climate and market conditions of each region.

A general pattern in the efficient designs for all regions is that when sorted by the highest operating income, the efficient designs incorporated LED lamps with a light intensity of 200 μmol m^{-2} s^{-1} coupled with CO_2 dosing at a rate above 100 kg ha^{-1} h^{-1}. Compared to High-Pressure Sodium (HPS) lamps, Light-Emitting Diode (LED) lamps can achieve a higher annual operating income with less electricity consumption. However, lighting is also the primary contributor to GHG emissions. When sorted based on the lowest GHG emissions, designs without lighting were identified for Langfang and Pingliang. For Jinshan and Weifang, LED lighting is essential to ensure a positive operating income under the low tomato price scenario.

Fogging is the recommended means of cooling for all regions, provided that a cooling system is selected in the efficient designs. For Jinshan, the recommended design components include a Venlo-type structure with glass as cover material, a small-capacity boiler (1.16 MW ha^{-1}), and transparent thermal screens. For Langfang, Weifang, and Pingliang, either a multi-tunnel structure or a Venlo-type structure can be considered. Applying whitewash during the summer is not recommended, except for in Langfang. When sorting by lowest GHG emissions, the preferred choice for Pingliang is a multi-tunnel structure with double PE as cover material and double-layer thermal screens, probably due to the region's cold winter and ample solar resources.

6.3 **Business and policy implications**

6.3.1 Policy implications

The findings of this dissertation present several implications for policy makers in designing new policies for China's high-tech greenhouse sector. This section summarizes the policy recommendations, focusing on subsidy policies and the non-financial support the government could provide to facilitate the development of this sector.

Subsidy policies play an essential role in the development of the greenhouse sector. First, subsidies are crucial for ensuring the economic feasibility of greenhouse investments in specific regions (Chapter 2). Second, the availability and prospective phasing-out of subsidies could induce early investment in high-tech greenhouses (Chapter 4). These two observations might explain the initial surge in investments and subsequent abandonment of high-tech greenhouses during the early years: an investor who overestimates the economic return of a greenhouse investment and simultaneously anticipates the subsidy scheme to be short-lived may rush into an economically infeasible investment. Such investment behaviour could undermine the sustainable development of the sector. If an investment is discontinued, not only are sunk costs lost, but also valuable learning opportunities. High-tech greenhouse operations are complex and involve steep learning curves. Management experience and increased efficiency can sometimes only be gained through learning by doing (Foster & Rosenzweig, 1995). To avoid such premature investments triggered by the anticipation of the subsidy scheme's termination, the government could foster stable expectations among investors by clearly stating the conditions or the time frame for the phasing-out of such subsidies, or by confirming the continuity of the subsidy scheme if it is intended to be permanent. Additionally, the government could explore alternatives to the existing lump-sum upfront subsidy, such as annual operational subsidies that are contingent on the sustained operation of the greenhouse. However, as this thesis did not delve into the impact of alternative subsidy forms, the discussion will not expand in that direction.

The encouragement of regionally suitable greenhouse designs could be achieved through region-specific subsidy policies. Rather than subsidizing a broad range of climate control technologies, these policies should focus on technologies that are well-suited for individual regions. As outlined in Chapter 3, the suitable greenhouse designs vary across regions. For instance, the Venlo-type glasshouse was the most suitable structure for Jinshan. The multi-span greenhouse may be a more appropriate choice for regions like Langfang and Pingliang. Double-layer thermal screens are advantageous in colder regions such as Langfang for energy-saving purposes. Moreover, LED lighting and CO_2 enrichment should be promoted as a bundled technology due to their synergistic effect on enhancing economic returns.

In addition to providing subsidies, the government can also support the growth of the greenhouse sector through various non-financial supports. Chapter 5 reveals that investors and suppliers often place little importance on the trialability of new technologies, stating that on-farm trials are rarely conducted in commercial greenhouses. Consequently, the results of government-funded demonstration programs serve as information sources for them to learn about new technologies. Therefore, the government should invest more resources in technology demonstration and provide timely information to reduce uncertainty among stakeholders about factors such as yield and quality effects, input costs, and practical guidance on the use of the technologies.

Energy prices significantly influence the profitability of greenhouse production, especially for greenhouses that rely on liquid natural gas (LNG) for heating (Chapter 2). Unlike pipeline natural gas, the end-user price of which is state-regulated and relatively stable, the prices of imported LNG are volatile (Paltsev & Zhang, 2015). One way to decrease energy costs is to utilize residual heat by locating greenhouses near facilities such as power generation factories. This strategy has already been implemented in some Chinese greenhouses. In the absence of residual heat, pipeline gas is a good alternative. However, this requires access to pipeline infrastructure, the construction costs of which may be prohibitive for many greenhouse investors. One approach is to cluster new greenhouses in areas in close proximity with existing pipeline networks. Such agglomeration allows not only for cost-sharing of pipeline infrastructure, but also fosters knowledge-sharing and accelerates innovation, as observed in the Dutch horticulture sector (Korthals Altes & van Rij, 2013). It should be noted that the holistic planning of high-tech greenhouses cannot be accomplished by the Bureau of Agriculture and Rural Affairs alone. It requires coordinated efforts of multiple agencies, including the Bureau of Housing and Urban-Rural Development, which is responsible for planning and constructing urban natural gas pipeline networks (Dong et al., 2017).

The results of Chapter 5 show that policy makers place higher importance on the environmental impacts of technologies than other stakeholders. During our interviews, several investors and growers indicated that they would give greater priority to the environmental impacts of technologies if there were more stringent regulations in place. Currently, regulations for China's horticulture sector focus mainly on plastic film recycling, drainage recycling, waste disposal, and chemical use. There are no regulations on energy use or GHG emissions, except for a ban on the use of coal for heating. Research on the Dutch horticulture sector suggests that stricter environmental regulations have reduced the technical inefficiencies of greenhouse firms (van der Vlist et al., 2007). This finding may have implications for China's greenhouse sector, especially concerning the use of lighting. LED lighting is not only more cost-effective, but also produces fewer GHG emissions than HPS lamps (Chapter 3). Despite these advantages, HPS lamps remain more widely used in Chinese greenhouses, probably due to their lower upfront costs. Implementing stricter regulations on energy use could potentially incentivize a shift towards LED lighting. This shift would be economically beneficial to greenhouse firms in the long term and would also make the sector more sustainable.

If policy makers want to improve the monitoring of environmental impacts, they could establish national standard guidelines for assessing the environmental footprint of greenhouse firms. In 2017, Beijing introduced a regional guideline for the GHG emissions accounting of protected agricultural enterprises. The scope of this guideline is refined to emissions generated from the use of electricity, heat, fuel for machinery, and nitrogen fertilizer. When developing a national guideline, policy makers should consider whether to include additional stages, such as storage, packaging, distribution, and retailing, as these constitute a more complete life cycle of horticultural products.

6.3.2 Business implications

In Chapter 5, interviews with investors indicated that before entering the greenhouse sector, they typically grapple with three questions: where should the greenhouse be located, which greenhouse design should be selected, and what are the expected economic returns? Chapters 2 and 3 addressed these questions. Using a representative glasshouse design as a reference, Chapter 2 presented the probability distribution of NPV of a glasshouse investment for tomato production in four regions. Building on the bio-economic model developed in Chapter 2, Chapter 3 further explores the optimal greenhouse designs.

Based on insights gained from Chapter 2 and 3, it is clear that the location matters. Pingliang's year-round production cycle allows it to achieve higher yields with less gas use. When it comes to selecting a greenhouse design, the Venlo-type glasshouse seems to be the optimal choice for Jinshan. Meanwhile, both the Venlo-type and multi-tunnel plastic greenhouse are viable options for Langfang, Weifang, and Pingliang. In areas with cold winters and high energy prices, a double-layer thermal screen can be an optimal choice. For investors with abundant capital and stable sales channels, investing in LED lighting coupled with CO_2 dosing can greatly increase yield, leading to higher profit. It is worth noting that although HPS lighting is a more common option in Chinese greenhouses due to its lower upfront costs, when one accounts for its short lifespan and the higher electricity consumption, LED lighting is more economical in the long run.

Seeking price differentiation based on product quality and safety is essential for ensuring high and stable revenues. Chapter 2's break-even analysis indicates that a 20-40% increase in tomato prices could make a greenhouse investment in Jinshan and Weifang profitable, even in the absence of subsidies. Before committing to a greenhouse investment, investors should carefully evaluate their sales channels. Establishing a strategic alliance between greenhouses and retailers through agro-food supply chain integration could be a promising approach (Zhao et al., 2021). While some larger greenhouse firms in China have successfully established direct purchasing arrangements with retailers, not all have managed to do so. Another important consideration is access to affordable energy, especially for heat-loving crops such as tomatoes. By strategically locating the greenhouse near sources of residual heat or natural gas pipelines, investors can mitigate the risks associated with energy price fluctuations.

Sensors and robotics suppliers can develop market strategies aligned with the preferences of different stakeholders. For example, sensor technologies are characterised by a low observability, whereas investors and policy makers prioritize this characteristic (Chapter 5). This discrepancy may eventually hinder the adoption of sensor technology. To enhance the observability of their products, sensor suppliers could organize workshops and encourage early adopters to share their successful experiences. As the high initial cost of robotic technologies is likely to be a primary barrier to their adoption, a leasing model may be more acceptable than outright ownership. Growers are more concerned with the trialability and compatibility of a technology (Chapter 5). When approaching growers, suppliers should focus on these concerns. They could offer live demonstrations and provide additional support to help growers integrate these technologies seamlessly into their work routines.

6.4 Limitations and future research

A variety of methods and data sources were used to achieve the research objectives of this thesis. This section reflects on the modelling choices, data and theory used and the methodological choices made in achieving the specific research objectives.

The bio-economic model developed in Chapter 2 forms the foundation of the analysis throughout this dissertation. The INTKAM-KASPRO model has been validated for a wide range of climate conditions, including in Shanghai, China (Luo et al., 2005a). However, the model also has several assumptions which may not always hold in reality. The INTKAM model assumes that irrigation, fertilization, disease and pest control, and crop handling are managed optimally (Salm et al., 2023). Additionally, the model assumes the use of mature plant seedlings at the transplant stage, with the first flowers already appearing on the plant. This may not be the common practice in Chinese greenhouses. These assumptions could explain the gap between the model's predicted yield and actual yield. This yield gap was accounted for in our analysis by applying a 5% loss rate on the predicted yield. In retrospect, this may have been underestimated, a loss rate of 10% or even a 15% loss rate may have been more realistic. Moreover, our analysis calculated revenue solely based on yield, while in commercial production, both yield and quality jointly determine the greenhouse revenue. A more realistic modelling approach could incorporate a tomato quality model into the biophysical model, as suggested by Vanthoor et al. (2011).

Economies of scale were not taken into account in the analysis of this dissertation. A study of Dutch greenhouse firms shows that the unit costs of energy, labour, and capital investment vary with the size of the greenhouse. Larger greenhouses usually have lower per unit energy costs and can obtain higher output prices (Los et al., 2019). The per unit labour and miscellaneous costs used in this dissertation were derived from the accounting data of a 1.4-ha greenhouse in China. Large greenhouses of more than 20 ha are emerging in China. The per unit costs of these larger greenhouses may differ from those used in this dissertation. Future studies could take into account economies of scale and further investigate the optimal size for greenhouse production in China. Such an analysis would require data from multiple greenhouse firms with detailed cost and production data for each firm. To our knowledge, no such dataset exists for the Chinese greenhouse sector.

Following the publication of Chapter 2, feedback from two growers indicated that the tomato prices in the model were higher than what they received for their products. This discrepancy is likely to be due to the 50% premium added to 2021 tomato prices. The premium was included based on the assumption that tomatoes produced in high-tech greenhouses are premium varieties, which would be sold through high-end sales channels. However, this is not always the case. Not all greenhouse firms have access to high-end sales channels. Despite the potential limitation of overestimating tomato prices, this concern has been partially addressed by including a break-even analysis in Chapter 2 and by considering a low tomato price scenario in Chapter 3.

This dissertation has partially captured the complexity of the behavioural components, with Chapter 4 focusing on strategic investment decisions under policy uncertainty and Chapter 5 examining stakeholder preferences. However, the economic analysis in this dissertation contains assumptions that may not always mirror real-world investment behaviour. For example, the constant discount rate used in Chapters 2 to 4 assumes that investors have a constant time preference. However, empirically observed discount rates are often not constant, but appear to decline over time (Frederick et al., 2002). Greater descriptive realism can be achieved by relaxing the constant time preference assumption, for example by using hyperbolic discounting (Frederick et al., 2002).

Chapter 2 presents break-even points determined by setting the expected NPV equal to zero, presuming that investors are risk-neutral. This may not necessarily represent the risk attitudes of real-world investors, as many Chinese agricultural decision-makers tend to be risk-averse

(Jianjun et al., 2015; Mao et al., 2019). Future work could delve into the risk attitudes of Chinese greenhouse investors. Incorporating risk aversion into the bio-economic model is relatively straightforward. The degree of risk aversion can be quantified through the Arrow-Pratt coefficient of relative risk aversion (Pratt, 1964). When combined with the variance of the economic returns of greenhouse investment (which can be derived based on the probability distribution of NPVs), a risk premium associated with the investment could be calculated.

The bio-economic model currently does not take into account growers' adaptive management strategies in response to price risks. In practice, growers may adjust input levels based on the input and output prices they observed during the growth season. An empirical study shows that Dutch greenhouse growers adjust their climate management strategies to reduce energy use when energy prices are high (Los et al., 2021). Future studies could capture these nuances by incorporating dynamic greenhouse management strategies that respond to energy and tomato prices.

Future work could investigate different forms of subsidy schemes and their impact on greenhouse investments. The subsidy scheme considered in this thesis is a lump-sum subsidy that is paid off at the beginning of a greenhouse investment. The Chinese government likely recognized the inefficiency of the current subsidy scheme. In 2020, the MOA of Beijing introduced a subsidy scheme based on the production outputs, but it is currently limited to traditional vegetable production farms. The National Development Plan for Modern Protected Agriculture (2023-2030) released in 2023 encourages local governments to implement reward-based subsidies (known as 以奖代补). However, the plan does not provide clear details regarding the qualifying criteria for receiving these rewards.

6.5 Main conclusions

- The economic feasibility of investing in a tomato greenhouse varies across regions due to differences in regional climate and market conditions. Considering a representative Venlo-type glasshouse, the mean NPV is 477.0 ¥ m^{-2} for Pingliang, −593.7 ¥ m^{-2} for Jinshan, 29.4 ¥ m^{-2} for Langfang, and −957.8 ¥ m^{-2} for Weifang (Chapters 2 and 3).
- The economic feasibility of greenhouse investments is highly uncertain due to price and policy uncertainty. This is evident from the broad range of NPVs. Specifically, without subsidies, the NPV in Jinshan ranges from −829.4 ¥ m^{-2} at the 5^{th} percentile to −355.5 ¥ m^{-2} at the 95^{th} percentile. In Langfang, the range is from −301.2 ¥ m^{-2} at the

5th percentile to 347.8 ¥ m^{-2} at the 95th percentile. In Weifang, NPVs vary from −1231.0 ¥ m^{-2} at the 5th percentile to −705.8 ¥ m^{-2} at the 95th percentile. In Pingliang, the range is from 182.0 ¥ m^{-2} at the 5th percentile to 749.3 ¥ m^{-2} at the 95th percentile (Chapters 2 and 4).

- Subsidies exert a twofold impact on greenhouse investments, affecting not only the economic feasibility but also the timing of such investments. For example, a subsidy of 50% of the initial investment costs could change the mean NPV of a tomato greenhouse investment in Jinshan from −593.7 ¥ m^{-2} to close to break-even. In addition, the expectation of a future phasing-out of a subsidy can create a strong incentive for early investment in greenhouses (Chapters 2 and 4).
- The optimal greenhouse design differs by region in China. For Jinshan, the recommended design components include a Venlo-type structure with glass as cover material, a small-capacity boiler, and transparent thermal screens. For Langfang, Weifang, and Pingliang, either a multi-tunnel structure or a Venlo-type structure can be considered. Applying whitewash is not recommended, except for in Langfang (Chapter 3).
- The choices of lighting, structure, thermal screen, and CO_2 dosing rate were among the most influential factors on operating income. Lighting is the primary contributor to GHG emissions, while the use of thermal screens can effectively reduce GHG emissions (Chapter 3).
- The observability of technology is highly valued by investors, technology suppliers, and policy makers. Meanwhile, growers place a higher emphasis on the technology's trialability and compatibility. Compared to other stakeholders, policy makers assign greater importance to the technology's environmental impact (Chapter 5).
- The deleafing robot received the lowest overall performance score across all stakeholder groups. The leaf temperature sensor has the highest overall performance score among growers and policy makers. The scouting robot and the harvesting robot received the highest overall performance scores among investors and suppliers, respectively (Chapter 5).

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Summary

Despite the rapid development, there is an ongoing debate about the economic feasibility of high-tech greenhouses in China. The designs of these greenhouses are often not adequately adapted to the local climatic and market conditions in China. Price and policy uncertainty adds further complexity to greenhouse investment decisions. As the greenhouse sector transitions towards increased digitalisation and automation, understanding the preferences of key stakeholders is essential to facilitate the further adoption and diffusion of emerging sensor and robotic technologies. The objective of this thesis was to assess the economic feasibility of greenhouse investments and to identify greenhouse designs, as well as sensor and robotic technologies, that align with the preferences of multiple stakeholders.

Chapter 2 assessed the economic feasibility of a greenhouse investment for tomato production. Taking into account fluctuations in tomato and natural gas prices, a Monte-Carlo simulation approach was used to obtain the probability distributions of the Net Present Values (NPVs) of a representative Venlo-type glasshouse for cherry tomato production in four locations: Jinshan (East China), Langfang (North China), Weifang (East China), and Pingliang (Northwest China). The economic outcome for such an investment varies across regions, with a mean NPV of 477.0 ¥ m^{-2} for Pingliang, −593.7 ¥ m^{-2} for Jinshan, 29.4 ¥ m^{-2} for Langfang, and −957.8 ¥ m^{-2} for Weifang. The economic feasibility of greenhouse investments is highly sensitive to fluctuations in tomato and natural gas prices, as indicated by the wide distribution of NPVs.

Chapter 3 identified several optimal greenhouse designs in terms of both economic and environmental performance for both policy makers and investors for the four locations in China. The bio-economic model developed in Chapter 2 was used to simulate the yield, energy use, and economic performance of different greenhouse designs. A genetic algorithm was used to explore the large solution space to reduce the computational effort. The overall performance of the greenhouse design was evaluated using a directional distance function, which incorporates

stakeholder priorities for economic and environmental performance through the directional vector. The results identify several greenhouse designs that were found to be efficient in terms of economic and environmental performance for both investors and policymakers across various price scenarios. The choices of lighting system, structure, thermal screen, and CO_2 dosing rate were among the most influential factors on operating income. Lighting is the primary contributor to GHG emissions, while the use of thermal screens can effectively reduce GHG emissions.

Chapter 4 examined how the uncertainty in output prices and the potential phasing-out of the subsidy scheme affect the optimal timing of greenhouse investment in China. The study employed a real options approach and formulated the investment decision as an optimal stopping problem. The least squares Monte Carlo method was used to approximate the optimal investment timing and the value of waiting under various combinations of subsidy level, subsidy termination risk factor, and tomato price evolution process. The numerical illustration shows that uncertainty about the phasing-out of the subsidy scheme can significantly reduce the value of waiting and induce earlier investment. In addition, an increase in the subsidy level could reduce the value of waiting and encourage earlier investment. A combination of a high subsidy level and the signalling of subsidy termination can substantially reduce the value of waiting and create a strong incentive for early investment.

Chapter 5 evaluated five sensor and robotic technologies based on the technology attributes defined in the Diffusion of Innovation theory. Four stakeholder groups, i.e., growers, investors, technology suppliers, and policy makers, were identified. The Bayesian best-worst method was used to elicit stakeholder preferences and expert-rated technology scores for each attribute. A probabilistic overall performance score for each technology was obtained by combining stakeholder preferences with expert-rated technology scores. Stakeholders present heterogeneous preferences for the technology attributes. The observability of technology is highly valued by investors, technology suppliers, and policy makers. Meanwhile, growers place a higher emphasis on the technology’s trialability and compatibility. Compared to other stakeholders, policy makers assign greater importance to the technology’s environmental impact. The deleafing robot received the lowest overall performance score across all stakeholder groups. The leaf temperature sensor has the highest overall performance score among growers and policy makers. The scouting robot and the harvesting robot received the highest overall performance scores among investors and suppliers, respectively.

The main conclusions of this thesis are:

- The economic feasibility of investing in a tomato greenhouse varies across regions due to differences in regional climate and market conditions. Considering a representative Venlo-type glasshouse, the mean NPV is 477.0 ¥ m^{-2} for Pingliang, −593.7 ¥ m^{-2} for Jinshan, 29.4 ¥ m^{-2} for Langfang, and −957.8 ¥ m^{-2} for Weifang (Chapters 2 and 3).
- The economic feasibility of greenhouse investments is highly uncertain due to price and policy uncertainty. This is evident from the broad range of NPVs. Specifically, without subsidies, the NPV in Jinshan ranges from −829.4 ¥ m^{-2} at the 5^{th} percentile to −355.5 ¥ m^{-2} at the 95^{th} percentile. In Langfang, the range is from −301.2 ¥ m^{-2} at the 5^{th} percentile to 347.8 ¥ m^{-2} at the 95^{th} percentile. In Weifang, NPVs vary from −1231.0 ¥ m^{-2} at the 5^{th} percentile to −705.8 ¥ m^{-2} at the 95^{th} percentile. In Pingliang, the range is from 182.0 ¥ m^{-2} at the 5^{th} percentile to 749.3 ¥ m^{-2} at the 95^{th} percentile (Chapters 2 and 4).
- Subsidies exert a twofold impact on greenhouse investments, affecting not only the economic feasibility but also the timing of such investments. For example, a subsidy of 50% of the initial investment costs could change the mean NPV of a tomato greenhouse investment in Jinshan from −593.7 ¥ m^{-2} to close to break-even. In addition, the expectation of a future phasing-out of a subsidy can create a strong incentive for early investment in greenhouses (Chapters 2 and 4).
- The optimal greenhouse design differs by region in China. For Jinshan, the recommended design components include a Venlo-type structure with glass as cover material, a small-capacity boiler, and transparent thermal screens. For Langfang, Weifang, and Pingliang, either a multi-tunnel structure or a Venlo-type structure can be considered. Applying whitewash is not recommended, except for in Langfang (Chapter 3).
- The choices of lighting, structure, thermal screen, and CO_2 dosing rate were among the most influential factors on operating income. Lighting is the primary contributor to GHG emissions, while the use of thermal screens can effectively reduce GHG emissions (Chapter 3).
- The observability of technology is highly valued by investors, technology suppliers, and policy makers. Meanwhile, growers place a higher emphasis on the technology's trialability and compatibility. Compared to other stakeholders, policy makers assign greater importance to the technology's environmental impact (Chapter 5).

The deleafing robot received the lowest overall performance score across all stakeholder groups. The leaf temperature sensor has the highest overall performance score among growers and policy makers. The scouting robot and the harvesting robot received the highest overall performance scores among investors and suppliers, respectively (Chapter 5).

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When I first set foot in Wageningen in 2017 to start my master’s studies, I couldn't have imagined that six precious years of my life would unfold in this tranquil yet lively university town. The experiences I’ve had here have shaped me in many ways, and their impact will continue. Now, as I spend my final month here, I find myself whispering farewells to every familiar corner. The paths I’ve walked, the buildings where I’ve studied, the trees that stood outside my office window, and the people who have walked this journey with me—I’m deeply thankful to each one. Without their support, this journey would not have been as beautiful.

A sincere thank you to Alfons Oude Lansink, who I was fortunate to have as my promotor. Alfons is not only a brilliant scholar, but also an outstanding manager. Looking back now, I see that his excellent time management and encouragement were crucial to completing my thesis on time. I’m especially grateful to Alfons for his support during a difficult conflict in the first year of my PhD. When I was on the brink of quitting, Alfons respected my decision and stood by my side, ready to forgo some of the group’s interests for my own. This act of kindness showed that his care went beyond his role as group chair. He was a mentor who genuinely cared about the well-being of his students. His support has been a cornerstone of my PhD journey.

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Nicola Trevisan, my dear Nick, my xiaobao, we crossed paths just a few days after I received my PhD acceptance. Since then, you’ve been an unwavering companion on this journey. You saw me laugh; you saw me cry. You applauded for my smallest achievements; you gave me generous hugs during tough times. You have mastered the art of navigating my moods and always knew how to cheer me up. And let’s not forget your contribution as the head chef during those intense final months of thesis writing. I’m endlessly thankful for your patience, trust, and love, which have provided me with a sense of emotional security every single day. You have been my rock, my best friend, and so much more.

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About the author

Xinyuan Min was born on August 28, 1995, to a loving family in Tianchang, Anhui Province. After graduating from high school, she pursued a bachelor’s degree in horticulture sciences at China Agricultural University in Beijing. During her undergraduate years, Xinyuan discovered her interest in management and business through various internships.

This passion motivated her to further her education and led her to pursue a Master's degree in Management, Economics, and Consumer Studies at Wageningen University & Research (WUR). Throughout her master's studies, Xinyuan developed a strong inclination towards quantitative methods, especially simulation modeling.

For her master's thesis, Xinyuan applied an adapted relax and fix heuristic to address the shared pickup and delivery challenges in last-mile logistics in urban areas, which was conducted in the Operations Research and Logistics group at WUR. This research fueled her enthusiasm for simulation modeling, and promoted her to delve deeper into this field.

In Autumn 2019, Xinyuan embarked on her PhD journey in the Business Economics group at WUR. This PhD project seamlessly integrated her background in horticulture from her bachelor's degree with the quantitative methods expertise gained during her master's studies. The project was part of the “Big Data Quantification and Modelling for Modern Agriculture in China” project, a collaboration between Laukuaikei Agriculture Development (Shanghai) Company Limited (LAD) and WUR.

Having now concluded her PhD, Xinyuan is ready to contribute to the field by taking on the role of agricultural investment advisor at LAD. She will apply her knowledge of agricultural science and economics to real-world investment scenarios.

Xinyuan Min

Wageningen School of Social Sciences (WASS)

Completed Training and Supervision Plan

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
A1 Managing a research project			
WASS Introduction Course	WASS	2019-2020	1
Writing research proposal	WASS	2019-2020	6
Scientific writing	Wageningen in'to Languages	2020	1.8
'*Economic feasibility of glasshouse tomato production in China*'	9th EAAE PhD workshop, Parma, Italy	2022	1
'Multi-stakeholder multi-objective greenhouse design optimization in China'	EAAE Congress, Rennes, France	2023	1
PhD meetings	BEC	2019-2023	2
A2 Integrating research in the corresponding discipline			
Research methodology: from topic to proposal	WASS	2019	4
Quantitative data analysis: multivariate techniques, YRM 50806	WUR	2020	6
Institutions and Societal Transformation	WASS	2021	2
B) General research related competences			
B1 Placing research in a broader scientific context			
Economics of farm households	WASS	2019	1
Advanced microeconomics, UEC 51806	WUR	2020	6
B2 Placing research in a societal context			
Making impact: increasing the relevance of research through science-society interaction	WGS	2021	1
C) Career related competences/personal development			
C1 Employing transferable skills in different domains/careers			
Critical thinking and argumentation	WGS	2019	0.3
Brain friendly working and writing	WGS	2019	0.3
Competence assessment	WGS	2020	0.3
Supervising two MSc thesis	BEC	2022-2023	2
Teaching assistant	BEC 51806	2021	2
Total			**37.7**

*One credit according to ECTS is on average equivalent to 28 hours of study load

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