Crop Selection and Land Allocation under Uncertainty:

Multi-Product Multi-Objective Optimization

By

Musawer Zeb

Fall 2020-MS L&SCM-00000328128-NBS

Supervisor:

Dr. Waqas Ahmed

Department of Operations & Supply Chain

A thesis submitted in partial fulfillment of requirements for the degree of

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THESIS ACCEPTANCE CERTIFICATE

It is certified that final copy of **MS O&SC** thesis written by **Mr. Musawer Zeb** Registration No. **00000328128** of **2020** has been vetted by undersigned, found complete in all aspects as per NUST Statutes/Regulations/MS Policy, is free of plagiarism, errors, and mistakes and is accepted as fulfilment for award of MS degree. It is further certified that necessary amendments as pointed out by GEC members and foreign/local evaluators of the scholar have also been incorporated in the said thesis.

Signature of Supervisor with stamp: ______________

DR. WAQAS AHMED
Associate Professor
Program Head (Operations & Supply Chain)
NUST Business School. H-12. Islamabad.

Date: 07-8-23

Programme Head Signature with stamp: ______________

DR. WAQAS AHMED
Associate Professor
Program-Head (Operations & Supply Chain)
NUST Business School. H-12. Islamabad.

Date: 07-8-23

Signature of HoD with stamp: ______________

Dr. Mujtaba Hassan Agha
Professor
HoD Operations & Supply Chain
NUST Business School (NBS)
H-12, Islamabad, Pakistan.

Date: 07-8-23

Countersign by

Signature (Dean/Principal): ______________

Principal & Dean
Dr. Naukhez Sarwar
NUST Business School

Date: 07-8-23

I hereby state that no portion of the work referred to in this dissertation has been submitted in support of an application for another degree or qualification of this or any other University or other institutes of learning.

Student Name: Musawer Zeb

Signature: ____________________

Date: 07-8-23

Table of contents

List of figures

List of tables

Abstract

The agriculture sector plays an essential role in a country's development. This is a primary source through which the human's basic needs are fulfilled. Getting the maximum output of agricultural land is a challenge for professionals. By utilizing agricultural land resources effectively, the revenue is increased. This research aims to develop a mathematical model for sustainable production considering economic, environmental, and social factors under uncertainty. Addressing crop rotation in different areas is more critical to acquiring the fundamental goals and objectives by optimizing crop selection and land allocation optimally. Optimal results are computed by a mathematical programming model using MATLAB that deals with multi-objectives for multi-products under uncertain circumstances and ensure the high utilization of resources, fulfills national food security, provides sustainable production techniques, and creates job opportunities with human health safety. The Augmented Epsilon Constraint Method with lexicographic optimization has dealt with conflicting multi-objectives (including Profit, Job opportunities, and yield). The proposed model was validated with primary data from the farmers in the Peshawar district of Pakistan. The land is classified based on land types such as rainfed, irrigated, etc. This study compares the single cropping pattern with intercropping, considering the three objectives. Three crops, ladyfinger, tomato, and round gourd were selected along with their intercropping combinations. The result shows that intercropping of ladyfinger with a round gourd gives a high profit and yield, whereas the intercropping of tomato with ladyfinger creates more jobs. Labor is the leading crop-farming resource, contributing 53% to the total cost. The proposed approach of crop selection and land allocation with intercropping shows an increase in total revenue, job opportunities, and yield compared to the traditional approach that has been practiced for the last decade.

1. Introduction

Agricultural resources are a fundamental and primary resource and are absolutely necessary for all living organisms, and for many centuries provided benefits to people and their socio-economic (Fisher et al. 2017; Ahmed and Schmitz 2011; Du et al. 2022). In this sense utilizing land and water resources to fulfill food requirements and clothing needs of human being, the basis of political, economic, cultural developments and social history (Chatterjee, Tran, and Shaw 2016). The availability of this resourcing for farm management plays an essential role in that region. That incorporates crop types, the quantity of cultivated crops, allocation of crop, verity of crop and combination decisions are needed in order to optimize in the crop grooving season (Bhatia and Rana 2020a).

Nowadays, limited water resources and the shortage has become a remarkable factor that is restricting the social and economic development of arid and semi-arid land. Agriculture sectors consume a high ratio of water resources. According to (Kang et al. 2017) the consumption of agricultural water is more than 70% of water consumption in the world. Enhancing crop production, irrigation water is more crucial, and shortages can seriously affect agricultural production. Solving water shortage problems, maximizing the utilization of agricultural water, and water allocation are the future goals of sustainable development of water resource management (Zhang and Guo 2017). The conflict between increased demands for water and reduced supplies and water shortage led to severe barriers to socioeconomic development. Efficient water resource management saves water and is thus helpful in the promotion of sustainable development and addressing water shortage problems (Komakech et al. 2011).

The exponential increase in population, rapidness in urbanization, and the mind-boggling development in the economy have caused a huge ecological environment pressure, water demand and scarcity issues directly affect agricultural water resources, security of food, and prosperous development in different regions (Yu and Qingshan 2014). Moreover, the agricultural system has uncertainties that exist in parameters and the interrelationship they have; in product with mixed features of human interface and natural variation, such as the condition of cultivated land and available water, water transferring complexities, random rainfall, and water requirements of crops (Xie et al. 2013).

Expanding the agricultural resources, especially land and related activities such as the applications of pesticides and fertilizers that have been conceived as a primary and main source of agricultural nonpoint source (NPS) pollution, and to the natural water is a great threat (Strokal et al. 2015). Particularly agriculture sector is endangered by natural effects like climate change. And the changes in the performance of these affect livelihood income and food security. Thus, the performance of the agricultural sector is more important to farmers and indirectly to the rest of the population by means of the food supply chain. Globally the dynamics of food markets are stimulated by the proliferation and development of production and consumption of agricultural output in emerging economies. For sustainable development of the agricultural sector, it requires a decision support system for these questions (Balezentis et al. 2020).

1.1 Importance of agriculture in human life:

The agriculture sector is vital to human life as it gives people access to life's needs, including food, shelter, and clothing. According to the (FAO), agriculture provides livelihoods for approximately 40% of the global population and is the primary source of food for almost 7 billion people. Agriculture also plays a crucial role in the global economy. In 2020, the global agriculture market was valued at $8.3 trillion, and it is expected at a compound annual growth rate (CAGR) of 4.4% from 2021 up to 2028 (United et al.., 2022)

Furthermore, Agriculture has a considerable environmental impact, including water use, land use, and emissions of greenhouse gases. Sustainable agriculture practices can help mitigate these negative impacts and promote environmental conservation. In summary, the agriculture sector is essential to human life and is critical in providing food and other basic necessities, supporting livelihoods, driving economic growth, and promoting environmental sustainability FAO (2021). The state of food and agriculture in 2021: changing food systems for increased food security, enhanced nutrition, and affordable healthful meals for all (Jones and Ejeta 2016).

The agriculture sector plays a vital role in the lives of both humans and animals. Here are some of the key ways in which agriculture supports human and animal life (Pawlak and Kołodziejczak 2020). Agriculture is the primary source of food for both humans and animals. Without agriculture, it would be impossible to meet the basic nutritional needs of the world's population. Agriculture provides a wide range of food products, including grains, vegetables, fruits, dairy products, meat, and fish. The agriculture sector provides employment opportunities for millions of people in the whole world. Here is an estimation that over 1.3 billion people are employed in agriculture-related industries, which account for a significant portion of the global economy (Salimova et al. 2022).

In the economic development of any country, agriculture plays a critical role, particularly in developing regions where agriculture is the primary industry. Agriculture contributes to economic growth by providing raw materials for industries such as textiles, pharmaceuticals, and food processing. Agriculture is critical for maintaining the health of ecosystems and the planet as a whole. Proper agricultural practices can help prevent soil erosion, improve soil health, reduce greenhouse gas emissions, and conserve water resources. Agriculture plays a crucial role in providing healthy and nutritious feed for livestock, which in turn supports animal health and well-being. This is particularly important in developing countries where livestock is a vital source of protein and other essential nutrients. Agriculture can help maintain and even enhance biodiversity by preserving traditional farming practices, conserving crop genetic diversity, and protecting natural habits.

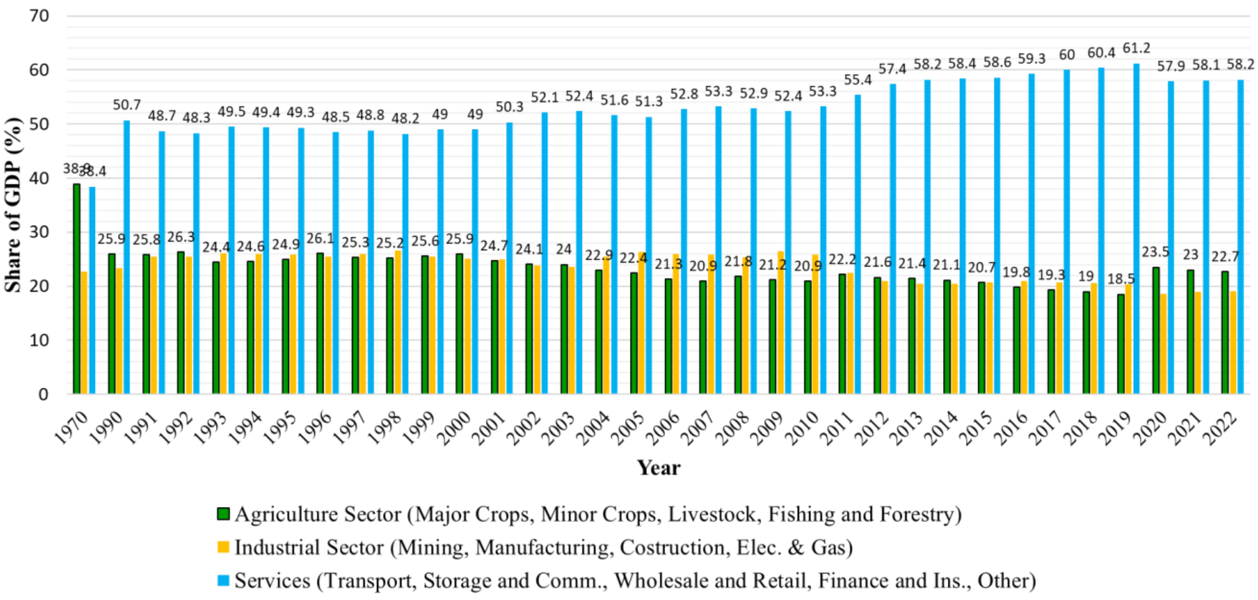


Figure 1.1: Sectoral share in GDP of Pakistan (%)

(Source: Federal Bureau of Statistics, 2022)

Pakistan's agriculture sector is the largest source of employment and income for those living in rural areas, making it essential for poverty alleviation, food security, and socio-economic development (Jan, Ashfaq, and Chandio 2021). Additionally, other essential manufacturing sectors rely on the performance of the agriculture sector for their raw materials. Although agriculture's contribution to Pakistan's GDP decreased to 22.7% in 2022, as shown in Figure 1.1, there is still potential to increase its impact through advanced agricultural technologies.

Although we can see the industries contribute more to Pakistan's GDP than the agriculture sector. However, the agriculture sector’s contribution to Pakistan's GDP should not be taken lightly. Throughout the 50 years agriculture sector and in the industrial sector have been mostly on the part with their contribution. The agriculture sector is responsible for producing a wide range of cash and food crops across 23.45 million hectares of land, including major and minor crops, herbs and medicinal plants, and other crops. Wheat is the most widely cultivated crop, occupying 34% of the total available cultivated land, followed by cotton, which is grown on 14% of the total cultivated land Tats.

1.2 Importance of crops:

Agriculture plays a significant role in the economy of Pakistan. One of the most important sectors contributing significantly to the country's GDP, employment and exports. It is the backbone of the country's economy, contributing approximately 22% of the gross domestic product (GDP) and employing over 38% of the country's workforce. Agriculture is the primary source of food in Pakistan, and it provides essential raw materials for the food processing industry. The country produces a wide range of crops, including wheat, rice, maize, sugarcane, cotton, and fruits, among others (Ahmad, Shah, and Ali 2019). Agriculture is a major employer in Pakistan, providing jobs for approximately 44% of the country's workforce.

Moving on, in Figure 1.1, we see Pakistan’s agriculture share in its GDP. It can be seen fluctuating throughout the years. However, in 2019 measures have been taken to increase its share. On the other hand, Figure 1.2 shows the crops share Pakistan's GDP. Just like Figure 1.1, it has fluctuated throughout the years; however, it has been increasing steadily since 2019. The sector also supports other industries, such as food processing, textile manufacturing, and livestock farming, creating more job opportunities. Agriculture exports contribute significantly to Pakistan's foreign exchange earnings. The country exports a variety of agricultural products, including rice, cotton, fruits, vegetables, and fish, among others.

Appiah et al. (2019) listed many of the food crops that are extremely vulnerable to rising average temperatures. Climate change is hurting the growth and exports of important agricultural commodities due to rising yearly temperatures, shifting rainfall patterns, floods, and decreasing water reservoirs. Pakistan is an agrarian developing country that depends on agriculture for income from foreign exchange, employment, and the growth of other manufacturing industries (Abbas and Waheed 2017). Cotton, leather, and rice constitute over 70.8% of the overall exports. Pakistan's key crops have had extremely slow and skewed growth in recent decades. The uneven growth performance of main crops might lower not only household earnings and job opportunities but also the performance of allied manufacturing businesses, exacerbated by the growing food insecurity problem. This variation in crop performance, among other things, can be attributed to climate susceptibility and change.

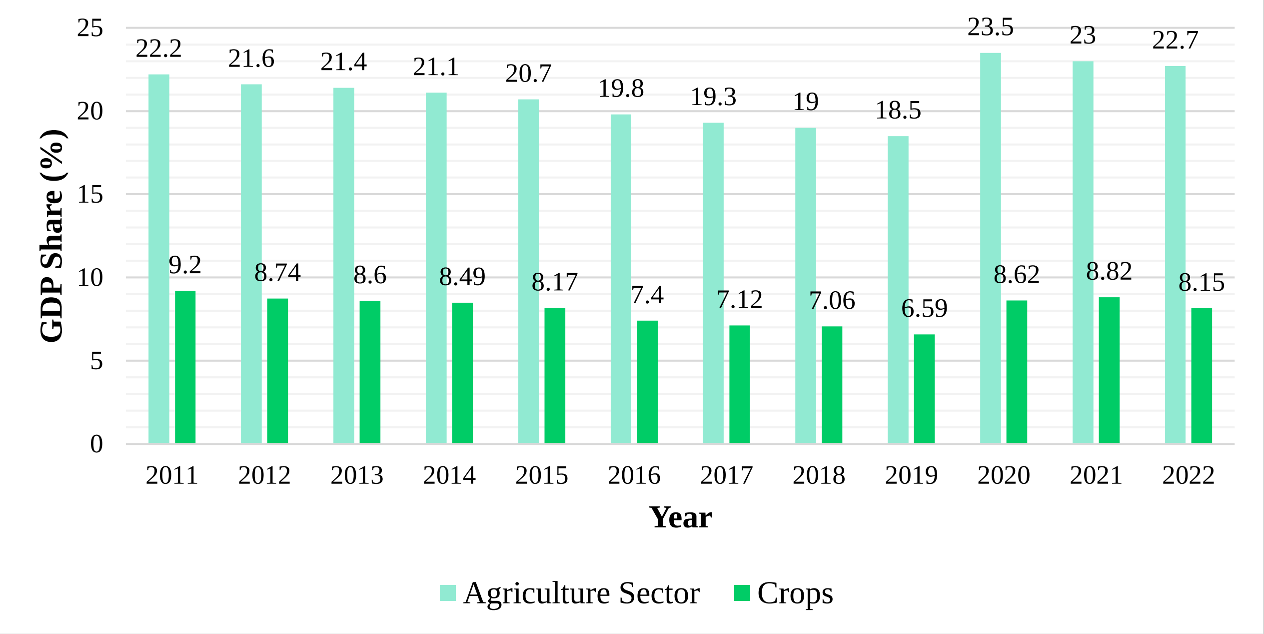


Figure 1.2: Agriculture and crops share in Pakistan GDP (%)

(Source: Federal Bureau of Statistics, 2022)

Temperature variations can take many forms, including high daytime and low nighttime temperatures, prolonged periods of exceptionally cold and hot weather, and variations in average temperature. These changes can cause flooding, glacier melt, diseases of plants, and pest assaults, all of which reduce crop yield. During the planting season of key crops, Pakistan's average yearly temperature remains considerably greater than the threshold temperature (Wahid et al. 2007). A recent research investigation looked at the impacts of climate change, particularly CO2 emissions, on wheat and maize crop yields in Pakistan's northern area of Khyber Pakhtunkhwa (KP). The study examined data from 1986 until 2015 using a second-generation cointegration panel approach. The results showed that greater precipitation had a large positive influence on cereal production, although rising average temperatures had little long-term impact (Jan, Ashfaq, and Chandio 2021).

1.3 Effect of climate change on crops:

If mitigating policies are not implemented, rising temperatures may deplete the frozen water reserves at Himalayan and Tibetan glaciers, exacerbating water scarcity. The average annual temperature change was negative from 1960 to 1997, and it has climbed exponentially since then (Yaseen et al. 2020). An upsurge in average temperature can manifest itself in a variety of ways, including a shift in normal daytime temperature, as well as a shift in the timing, severity, and length of extremely hot weather. The increased temperature throughout the growing season causes them to spend greater amounts of energy on breathing and less energy for growth.

There have been numerous studies conducted in Pakistan examining the impact of climate change, specifically CO_2 emissions, on the agriculture sector. One early study utilized panel econometrics to investigate the impact of climate change on food production across all provinces in Pakistan. Their findings indicated that even minor changes in climate had a negative impact on crop production. Agriculture production is highly sensitive to climate change due to its reliance on climate variables such as temperature and rainfall.

Temperature, precipitation, and sun radiation are all major influences on crop development and production. Climate change has been characterized by rising temperatures, altered precipitation patterns, and an increase in the likelihood of extreme weather events (Malla et al. 2022). Increasing temperature hastens crop phenological growth and lowers the growing season, potentially reducing agricultural output. Furthermore, dryness caused by decreasing precipitation poses a significant hazard to agricultural development. A deeper understanding of how crops react to climate change can give a scientific foundation for adapting to and reducing the effects of climate change (Lopes 2022).

1.4 Food security and farming techniques:

The worldwide economy is currently in peril as a result of the ongoing local and international lockdown for COVID-19. Many people have already lost their employment, and businesses have been shaky during the Corona era. In addition to educational institutions, banks, private institutions, and agriculture, practically all industries are experiencing economic downturns. The roles of contemporary technologies, the Internet of Things, and artificial intelligence in assisting the world in achieving economic success in the post-COVID-19 economic depression are undeniable. Food production must expand by 60% by 2050 to meet the world's food demands in the face of unpredictability, like as the COVID-19 pandemic and an aging population. Given the severity and isolation of COVID 19, strengthening food production and delivery networks is crucial to reducing hunger and resolving other issues (Saad, Hamdan, and Sarker 2021).

As the world's population grows by the day, with an estimated 9.6 billion people by 2050, there is an increasing need to adapt agriculture practices and technologies in order to maximize harvests while reducing human labor (Saad, Hamdan, and Sarker 2021). Urban smart vertical farming (USVF) is a way to secure food production that may be implemented in any adaptive reuse, retrofit, or new vertical buildings. Vertical farming allows for throughout-the-year crop production, more control over food security and biosecurity, and lower inputs, including water, herbicides, pesticides, and fertilizers (Al-Kodmany 2018).

The application of environmentally friendly technologies can help farmers combat the consequences of climate change, increase productivity, increase producer earnings, and improve household welfare. A number of developing nations have placed a focus on climate-smart agriculture technology as an intervention to enhance the living conditions of smallholder farmers. Food security is ensured via precision agriculture while environmental quality is maintained. The rice output was enhanced while crops were protected from natural calamities by farm management practices (Kc et al. 2021). An infrastructure-based technique called a "tunnel house" makes crop production possible over a longer period of time. Despite the fact that tunnel technology was first created in the industrialized world (Bhusal et al. 2020). The majority of growers who use tunnels do so using drip irrigation and plastic film for mulching. Additionally, they use pesticides (fertilizer, insecticides, herbicides, and fungicides) in a planned and effective manner to enhance soil fertility and grow vegetables of the highest quality (Yaseen et al. 2020).

Global issues related to food security are growing more and more significant. Rapid urbanization and industrialization, two anthropogenic phenomena, have put a demand on limited resources, including land and water. As a result, the world can no longer rely on conventional means to meet its demands as the danger to food security grows. To maximize dwindling natural resources, more innovative and technologically advanced ways must be used (Takle et al. 2013). Singapore has used technologies like vertical farming and aquaponics in urban farming, recovering nutrients from food waste, biodegradable food containers made from durian rinds, natural preservers, insect farming, microalgae, and meat from livestock as alternative protein sources to increase self-production of food and improve its food security. The limitations on land and natural resources that Singapore faces can be overcome by these technologies, which are adaptable in many nations. However, many of them are still in their infancy and face several obstacles that must be overcome before they can be broadly embraced and put into practice (Mok, Tan, and Chen 2020).

Intercropping is a crucial agroforestry technique that may enhance crop output and quality while simultaneously boosting biodiversity, the microclimate, and resource utilization. (Wen et al. 2020) studied intercropping for tea and three tea-fruit with soil environmental characteristics and tea quality. While the heavy metal level and pH value were in opposition to one other, the soil nutrients of the three intercropping patterns were greater than those of the single tea plantation. Additionally, there was a correlation between the sample time and the variation in pH and soil nutrients under intercropping patterns. The tea plantation with intercropping patterns had greater levels of free amino acids, lower levels of catechins, and a higher ratio of phenol to amino acids, all of which are favorable to the development of high-quality green tea. Soil nutrients were greater under the patterns of loquat-tea intercropping and citrus-tea intercropping than under waxberry-tea intercropping. For tea quality, citrus-tea intercropping is better than the other two intercropping patterns.

Intercropping maize with fodder cowpea is a commonly advocated method for increasing the economic value of the agricultural system and the efficiency of land usage, particularly in resource-constrained developing nations. As a tool for agricultural intensification, intercropping has been shown to be an essential technique for boosting land use effectiveness, elevating production gains, and raising the economic value of the agricultural system (Salama, Nawar, and Khalil 2022). Intercropping has recently been seen as a successful tactic for boosting the farming system's resistance to climate change risks. In order to fill the gaps in the food and feed supply, cereal-legume intercropping is a commonly advocated method, particularly in developing nations with limited agricultural inputs (Salama and Abdel-Moneim 2021). Low survival rates and low yields severely hinder commercial production of the medicinal herb Atractylodes lancea. When interspecific interactions are properly coordinated, environmental resources are used effectively, and survival and yield are all increased (Peng et al. 2021).

2. Literature Review

Agriculture resource utilization has been the focus of researchers. In literature the different approaches are used to deal with cardinal factors in field. However, as each of these previously conducted research lacked at least one of the (mentioned in Table 2.1) cardinal factors. Most of the researchers lacked the most important factor of intercropping, which has been covered in this research. Researcher worked for the management of water and soil resources to acquire maximum output of the available resources.

Implementing distinct methodologies and optimization programming like (Bhatia and Rana 2020a) used linear programming (LP) techniques to increase revenue by optimizing cropping patterns. Das et al. (2015) developed LP model to optimize water and land assets for sustainable irrigation. Najafabadi et al. (2019) implement a multi-objective structural programming model and robust optimization methods to optimize regional cropping pattern decisions. Ren, Li, and Zhang (2019) worked on the AHP in the agriculture sector under uncertain resources of water and land optimization and used multi-objective stochastic fuzzy programming.

Xie et al. (2018) have developed an inexact stochastic fuzzy programming model for agricultural resources to utilize the water and land resources under the uncertainty of effective rainfall. The main objectives were to manage the imprecise water consumption and random rainfall considering socio-economic development. Li, Fu, Singh, Liu, et al. (2020) defined a multi-objective Non-Linear optimization model to manage agricultural resources with tradeoffs between economic, social, and environmental considerations.

Qureshi, Singh, and Hasan (2018b) applied the fuzzy TOPSIS method, and (Mishra et al. 2019) used a multi-criteria decision-making (MCDM) technique for the selection of crop mix sustainability. To manage the agricultural water-land nexus system Sun et al. (2019) developed a possibilistic-flexible chance-constrained model that helps to understand the analysis for the trade-off between reliable customer satisfaction and system benefits. Due to the conflict of sustainability factors such as economic, environmental, and social management of agricultural resources are complicated.

Previous research studies focused on benefits maximization through the optimization of land and water resources. However, the theories of sustainable agriculture and cleaner agricultural production lead to the consideration of social and environmental effects, especially global warming and climate change (Zessner et al. 2017). The major source of greenhouse gas (GHGs) emissions is cropland, such as N_2O, CH_4, and CO_2 affect the air environment. Pollutants from agricultural residues like pesticides and chemical fertilizers enter rivers and affect the water environment, and its effect is of great concern. Consequently, it is essential to reconcile and harmonize the contradictions among the three main factors of sustainability, including economic, environmental, and social, in the system with limited resources of supply in order to promote sustainable agricultural development (Li, Fu, Singh, Liu, et al. 2020).

The primary element influencing the agricultural high-end equipment manufacture (AHEM) system's digitalization and decarbonization plan is digital green innovation (DGI). There are several barriers in the way of DGI, despite the fact that AHEM firms actively collaborate with university research institutions to produce high-end agricultural equipment. Additionally, the present literature has not thoroughly explored the integration of digital technology and green innovation from the standpoint of partner matching for the AHEM system (Yin, Wang, and Xu 2022). Therefore, the objectives of this study were to (i) provide an appropriate framework system for the AHEM system in general, (ii) quantify the academic research institutions' choice of DGI based on niche theory, and (iii) propose an extended niche field model coupled with fuzzy VIKOR model.

2.1 Multi-objective programming:

Multi-objective optimization in agriculture has been the subject of significant research over the past few decades. Many studies have focused on optimizing multiple objectives in crop production, livestock management, and other aspects of agriculture. Crop production is a vital component of agriculture, and optimization of crop production has been the focus of much research. Multi-objective optimization has been used to optimize different aspects of crop production, such as yield, water use, fertilizer use, and pesticide use. Kody, Bramesfeld, and Schmidt (2013) used multi-objective optimization to optimize the use of nitrogen fertilizer in maize production, considering both yield and environmental impacts. The study claimed that multi-objective optimization could significantly reduce nitrogen use while maintaining high yields and reducing environmental impacts. Similarly, the optimization of irrigation water use has also been a popular research topic. Multi-objective optimization has been used to optimize water use in different crops, such as wheat, maize, and soybean.

Hu et al. (2014) used multi-objective optimization to optimize irrigation scheduling for maize production in arid areas of China, considering both crop yield and water use efficiency. The study argued that multi-objective optimization could significantly improve crop yield and water use efficiency compared to traditional irrigation scheduling methods. The literature also discusses livestock management as another critical aspect of agriculture, and optimization of livestock management can improve production efficiency and animal welfare. Multi-objective optimization has been used to optimize different aspects of livestock management, such as feeding strategies, breeding programs, and health management. De la Cruz et al. (2018) used multi-objective optimization to optimize the feeding strategies for dairy cows, considering both milk production and methane emissions. The study claims that multi-objective optimization could significantly reduce methane emissions while maintaining high milk production. Environmental impact is an essential consideration in agricultural production, and multi-objective optimization has been used to optimize agricultural production while minimizing environmental impact.

Randall et al. (2007) used multi-objective optimization to optimize land use in a watershed, considering both agricultural production and environmental impact. The study found that multi-objective optimization could improve agricultural production while reducing soil erosion and nutrient loss. A multi-objective optimization is a promising approach for improving agricultural production by considering multiple objectives simultaneously. The optimization of crop production, livestock management, and environmental impact are some of the key research topics in the field of study. Multi-objective optimization has been used to optimize different aspects of agriculture, such as yield, water use, fertilizer use, pesticide use, feeding strategies, breeding programs, and health management. The optimization of agriculture is essential to meet the increasing demand for food and other agricultural products while minimizing environmental impact.

The agricultural sector is particularly susceptible to natural factors such as climate change, which can impact food security, income, and livelihoods. The performance of agriculture is crucial to farmers and the wider population through the connections across food supply chains (Gregorioa and Ancog 2020). The growth and expansion of consumption and production of agricultural products in emerging economies, particularly in Asian countries, have influenced the dynamics of global food markets. Many researchers opt for Linear Programming as it is a suitable method to assess solution feasibility in complex fields. The Simplex algorithm, created by Dantzig, is employed to resolve Linear Programming optimization issues. Initially, the Linear Programming technique establishes a feasible primal basis, which is then maintained through pivot operations to ensure the feasibility of the basis and to determine the objective function's value.

Alotaibi and Nadeem (2021) formulated a Linear Programming model for an agricultural farm that incorporates a crop rotation policy, aiming to maximize the overall gross margin. The findings indicate that adopting this strategy led to an increase in farm revenues compared to conventional crop practices. Given the rising demand for food and technological progress in the sector, scholars are now exploring sustainable growth in addition to higher crop yield. Boyabatlı, Nasiry, and Zhou (2019) introduced a dynamic model for the allocation of farmland for multiple crops. The research highlighted that the farmers encounter various uncertainties related to farm revenues. Hence, they developed a model that considers crop decisions in the face of revenue uncertainty. Effective farm management, particularly with limited water and land resources, is a critical aspect of the agricultural sector. Crop patterns for cultivation depend on the availability of arable land, and growers need to choose the optimal pattern to maximize crop yield.

Increased production, biodiversity, and the provision of environmental services are all simultaneously improved by multifunctional and varied agriculture, which can respond to conflicting pressures and demands. This may be supported by the use of digital technology, which can be used to plan and administer resource-conscious and contextually appropriate agricultural systems. To illustrate a strategy that uses digital technology to facilitate decision-making toward diverse and sustainable agriculture, (Mouratiadou et al. 2023) proposed the Digital Agricultural Knowledge and Information System (DAKIS), studied the literature to identify shortcomings in the existing generation of tools and jointly defined the criteria for a knowledge-based decision-support tool with stakeholders before developing the DAKIS.

The review's findings indicate that there are persistent issues with considering ecosystem services and biodiversity, fostering interaction and collaboration between farmers and other players, and with connecting various spatiotemporal scales and sustainability levels. To address these issues, the DAKIS offers a digital platform that assists farmers in making decisions about the use and management of their land using an integrated spatiotemporally explicit method that analyzes a variety of data from different sources. In order to address the various factors influencing agricultural land use and management design, such as natural and agronomic factors, economic and policy considerations, as well as socio-cultural preferences and settings, the approach integrates remote sensors, artificial intelligence, modeling, stakeholder-stated demand for ecosystem services and biodiversity, and participatory sustainability impact assessment.

Conflicts between agricultural production and profitability on the one hand, and the supply of biodiversity and ecosystem services (ESS) on the other, may result from a variety of divergent pressures and demands. Theoretically, different agricultural systems created to improve ecosystem multi-functionality should be better equipped to satisfy such varied aims, especially at the landscape level, by delivering a variety of amenities while promoting biodiversity and ecosystem health and resilience (Kremen, Iles, and Bacon 2012), (Pérez-Soba et al. 2008).

2.2 Water management

Lakshmi et al. (2021) introduced three approaches for crop allocation based on water resources. The first approach assumes sufficient water availability, the second allocates crops under a limited water supply with predetermined allocation, and optimal water distribution is critical for maximizing profits. The last approach allows flexible crop patterns and combination selection under water scarcity, for which a multi-objective Linear Programming model has been proposed in multiple pieces of research, aiming to maximize revenue and minimize input costs while simultaneously considering both water and land resources. The findings of multiple pieces of research demonstrate that this optimization technique significantly enhances farmers' profits by efficiently allocating land and water resources.

Existing literature argues that to increase farm revenues through optimizing the irrigation pattern. Irrigation has traditionally been based on cropping scenarios. However, some researchers believe that a multi-criteria approach is the most effective tool for optimizing farm resources. By addressing multiple objectives simultaneously, multi-objective programming can provide a trade-off among solutions. Bhatia and Rana (2020a) formulated a model to increase farm revenues using a multi-objective technique to optimize the irrigation pattern. The basis for classification was kept consistent throughout the development of the model and to optimize available resources. The net benefit of the farm was also considered as a model constraint, not a part of the objective function.

Proper warehouse management and keeping inventory have become increasingly necessary with the growth of production needed to feed the growing population. Taye et al. (2021) developed a mathematical model using a multi-objective approach to evaluate the feasibility of a region. The research provides insight into how a multi-objective technique can optimize farm resources.

Typically, crop planning is studied as a single-objective problem with the goal of maximizing farm revenues and minimizing crop production costs by listing constraints. Wang, Ye, and Sharma (2021) developed a mathematical model that studies the high impact of crop rotation on decision-making and integrated crop-livestock scenarios. The model integrates various farm activities, including livestock management, crop allocation, yield quantity, mechanized cost, and other operational activities of the farm. The study results reveal that an integrated crop-livestock scenario shows a significant role in determining an optimal plan. Researchers claim that crop rotation pattern is more sensitive and highly risky and should be precisely planned for maximizing farm revenues.

To meet the increasing demand for crop production, efficient farm resource allocation is crucial. Bhatia and Rana (2020a) proposed a Linear Programming method that allocates a combination of five crops to increase crop yield. The objective of the model used in the literature is to efficiently allocate resources to maximize crop productivity per hectare and increase the area under cultivation. The agriculture sector uses most of the available water for irrigation, which has resulted in an increased demand for water allocation in farms. Ren, Li, and Zhang (2019) proposed a multi-objective allocation model for water that optimizes the economic, ecological, and social benefits of a region. The model used in existing literature considered different types of water (groundwater and surface water) for irrigating purposes and was applied to Minqin's irrigation areas Gansu Province, China. The model results indicate that sustainable water allocation in water-deficient regions can be achieved through the model.

Minh et al. (2019) and Qureshi, Singh, and Hasan (2018a) addressed the issue of sustainable selection of crop mix in India by utilizing multi-criteria decision-making (MCDM) approaches, while Rao et al. (2019) shows the key indicators for the development of climate-resilient agriculture in India. (Orojloo, Shahdany, and Roozbahani 2018) created a fuzzy MCDM technique to water management for the development of sustainable agriculture. Sulewski, Kłoczko-Gajewska, and Sroka (2018), Kelly et al. (2018), and used FADN data to evaluate the sustainability of agricultural farming systems. Kamali et al. (2017) proposed a multi-criteria framework for assessing the sustainability of distinct farming methods.

The use of mathematical programming and multi-criteria decision-making techniques have been extensively applied in various studies to optimize resource allocation and crop selection and assess sustainability in agriculture. However, there has been a lack of integrated approaches that consider various quantitative measures for sustainability, including crop diversity and water footprint. To address this gap, multiple authors propose an integrated approach using mathematical programming to study optimal crop mixes considering different scenarios in Lithuania, a new EU member state, with a focus on promoting organic farming. Multi-criteria analysis using SAW, TOPSIS, and EDAS techniques are applied to rank the scenarios based on economic and environmental aspect. By establishing a paradigm for analyzing scenarios based on the water-economy nexus, the research has added to existing research on sustainable agricultural management.

Harp et al. (2023) create and implement a strategy to decide which farms should receive irrigation system modifications in order to improve the water quality of agricultural drain discharge. The method takes into consideration the attenuation of pollutants transferred from fields to drain-network outlets over intricate drainage networks. The method generates an irrigation system upgrade Pareto-optimal cost curve that strikes a balance between maximizing the decrease of drain-outlet loads and reducing upgrade implementation costs. In order to arrange drain-network data, route drain-network flow channels, and create objectives and constraints for multi-objective optimization, the technique makes use of a graph-theoretic data structure.

In locations with water shortages, the equitable distribution of water resources is crucial for reducing imbalances between supply and demand. Digitization is happening faster because to current information technology's ongoing growth. Technical help is available through digital water networks, and its use is expanding. Du et al. (2022) provides a new operational implementation model of multi-objective water resource management based on a digital water network and uses the proposed approach to allocate water resources in the Heihe River basin in Xi'an, Shaanxi Province, based on the conventional method of water resource allocation along with the development of modern information technology.

2.3 Economic aspect:

The literature argues that one way to maximize profits of the agricultural sector is to change the cropping pattern in a way that considers economic goals, environmental impacts, and regional production factors like water and land. The cropping pattern is based on macro policies, indigenous knowledge and experience of farmers, and the eco-physiological principles of agricultural production (Tirkolaee et al. 2020). Choosing agronomic activities to meet different objectives requires a balance that is created by the decision-maker between inter-conflicting decisions and output results.

Decision-making and planning are not easy tasks in situations like multiple objectives faced by unit managers. Mathematical programming techniques, such as multi-objective programming (MOP), have prestigious advantages in resulting in an optimal cropping pattern that includes decision variables, objective functions, and constraints. The MOP decision-making model aims at optimizing objective functions; these issues rarely have unique solutions; the decision-maker selects the best options from a set of efficient responses. Studies have applied MOP to minimize the use of irrigation water, chemical fertilizers, and chemical pesticides to maximize productivity.

Existing literature argues that life-cycle assessment research has been conducted in the agricultural sector. These studies have targeted a limited range of classifications of impact and mostly focused on the warming potential index and CO_2 emissions. They have devoted less attention to courses affecting individuals and the cancer rate under investigation. The agricultural sector accounts for the majority of income and jobs in Lorestan, particularly in the province's east (Rehman, Ozturk, and Zhang 2019). In this region, rainfed and irrigated crops are grown, and a lack of adequate cropping patterns has resulted in lower production of crops, deterioration of the environment, and environmental repercussions on human health.

There has been little research on the mitigation of environmental impact on the health of people in cropping patterns and LCA-MOP integration via consideration of highest income while reducing ecological effects on humans, such as reducing carcinogen release, as well as land and water constraints for optimal crop allocation, is extremely beneficial to provide suitable cropping patterns. Adem, DÜNDAR, and ACER (2022) developed a mathematical programming approach that has been used in literature to compromise between increasing gross returns and decreasing the release of carcinogens and noncarcinogens, respiratory inorganics, depletion of the ozone layer, ionizing radiation, and respiratory organics as environmental problems that are affecting human life. The studies have provided useful information to develop appropriate strategies to minimize environmental impacts on humans while determining a cropping pattern considering multiple goals.

Existing literature argues that the scarcity of agricultural water and land resources has become a critical issue due to population growth and economic development, making it necessary to allocate these resources efficiently for sustainable development. Land-use allocation is important to guide decision-makers in assessing land demand for multiple crop types and identifying the best land spatial unit for each crop type. The agricultural land-use allocation process involves three stages: demand assessment, suitability evaluation of agricultural land, and spatial distribution of crop types.

Environmental and socioeconomic variables are considered when assessing agricultural land suitability, and the FAO has generated agricultural-specific maps of crop classifications for suitability utilizing spatial information on soil, topography, characteristics, and crop characteristics. Existing literature, however, contends that the fundamental limitation of FAO-based approaches is their poor settlement, which can be too coarse to meet research requirements at the irrigated district size (Gabr 2022). The goal of the allocation of agricultural land is to spatially allocate crop kinds to various spatial units in order to find the best land use plan. Optimization models such as linear programming, nonlinear programming, fuzzy programming, multi-objective optimization, stochastic optimization, and heuristic algorithms have been created; however, they have all overlooked the effective unification of quantity and space. The framework of least cross-entropy is used to define spatial crop optimization in this study.

Multiple research has combined multi-source data from satellites with limitations of ideal crop areas and agriculture cropping patterns to produce the integrated optimization model for the spatial distribution of crop cropping. The model is based on crop suitability geographic distribution, population density spatial distribution, and agricultural land use statistics. It can give an ideal cropping plan and analyze the optimal geographical distribution of agricultural products, which is useful for guiding actual production operations (Sakamoto 2020).

The model can be applied to allocate agricultural water and land resources for sustainable development. The study proposes a novel approach to optimize the allocation of water and land resources in agriculture under multiple uncertainties. The proposed approach integrates multi-objective stochastic fuzzy programming (MOSFP) and the Analytic Hierarchy Process (AHP) method to address the uncertainties related to water availability, crop yields, and prices.

2.4 Social and environmental aspect of land allocation:

The research in present whose study area is the Xiangjiang River Basin in China, where water scarcity and land competition between agriculture and urbanization are critical issues. The MOSFP model considers three objectives: maximizing net profits, minimizing water consumption, and maximizing land-use efficiency. The model also considers the uncertainties related to water supply, crop yields, and prices. The AHP method is used to determine the relative weights of the three objectives (Chen et al. 2022). The consequences depict that the proposed approach can optimize the allocation of water, land resources considering multiple uncertainties.

The optimal solution suggests that water should be allocated to crops with higher water use efficiency, such as fruit trees and vegetables, rather than to crops with lower water use efficiency, such as rice. The optimal allocation of land also suggests a shift towards high-value crops, such as fruit trees and vegetables, to maximize profits and land use efficiency. The study also conducts a sensitivity analysis to show the robustness of the new proposed approach using different scenarios. The results indicate that the approach is relatively robust to changes in water supply and crop yields but more sensitive to changes in crop prices.

Lu, Huang, and He (2012) Introduced a method for irrigation management of crops in China using simulation-based inexact rough-interval programming that considered multiple water sources and various constraints. Li, Li, and Huang (2012) developed a two-stage stochastic programming approach using interval parameter programming for irrigation optimization in Minqin County, China. Dong et al. (2012) integrated inexact modeling, interval parameter programming, and chance-constraint programming to develop a method for water resources optimization and land use management. Liu, Zou, and Wang (2020) proposed an inexact stochastic programming model for irrigation management in Yongxin County that utilized functional intervals, probability distribution functions, and conventional intervals to address uncertainties in parameters.

Tan et al. (2016) developed a robust interval fuzzy programming technique with risk-aversion and superiority-inferiority analyses to identify sustainable agricultural and industrial production strategies at the watershed scale. Sun et al. (2016) proposed an integrated approach for water resources allocation management within a generic life cycle assessment framework, combining operational research and uncertainty analysis approaches.

Cropland is a major contributor to greenhouse gas emissions, which are related to agricultural water and land resource utilization. Farming practices also introduce pollutants into rivers, which is a major concern. Fairly distributing limited agricultural resources to different users is important for regional stability. Existing literature argues that the multi-objective programming (MOP) is a promising approach for reconciling economic, environmental, and social factors in sustainable agriculture (Ferreira et al. 2012). Optimizing agricultural resources using MOP has become a hot topic, but few studies have considered the optimization of both water and land resources. Uncertainties, such as variations in hydrological elements and economic fluctuations, make optimal allocation of resources challenging.

Fuzzy set theory is a useful approach to express uncertainties in optimization models. Fuzzy credibility-constrained programming (FCCP) is particularly effective for agricultural water and land resources management, while intuitionistic fuzzy numbers (IFNs) have more flexibility dealing with uncertainties (Ren et al. 2020). Integrating FCCP and IFNs can address fuzziness in agricultural resources allocation under complex fuzzy environments. Using IFNs and FCCP, this paper creates an optimization model for allocating agricultural land and water resources under uncertainty. The model tries to obtain the best overall economic, environmental, and social consequences while dealing with the uncertainty of agricultural resource allocation. A real-world investigation in northeast China is used to validate the research.

Studies claim that determining the best way to allocate agricultural land and water resources is a complex task that involves natural resources, social, economic, and environmental factors. To achieve sustainable agriculture, multi-objective programming techniques can be used to allocate land and water resources, but most studies have focused on maximizing net system return or minimizing water consumption. However, to ensure sustainable agricultural development, it is important to consider the agricultural environment, especially the soil environment in crop lands (Liu, Zou, and Wang 2020). As per research, the use of fertilizers, pesticides, agricultural films, and machinery in food production can have negative impacts on the environment, including CO2 emissions, N2O and ammonia volatilization, and the release of NOx, CH4, and NH3 through straw burning. The cropland soil is a potential carbon sink that is affected by agricultural land and water management, as well as the soil tillage system.

Therefore, according to existing literature, it is essential to study these soil-environment impacts when agricultural land and water resources management to support sustainable agricultural management. Allocating agricultural land and water resources for the purpose of sustainable agriculture is a complicated process that involves various natural and social factors. However, most research has focused on increasing net system return or reducing water consumption without considering the impact of agricultural practices on the soil nature. Understanding the soil-environmental impacts of agricultural management is crucial for sustainable agricultural development (Rao et al. 2019).

2.5 Effect of climate change:

The increasing demands for agricultural land and products due to the growth of the world population and economy have led to the reclamation of a large amount of land for agricultural activities. However, the expansion of agricultural land areas and corresponding intensive agricultural activities have resulted in agricultural nonpoint source (NPS) pollution, which is a primary cause of water quality degradation. Existing literature argues that Nitrogen (N) and phosphorus (P) are the major pollutants released from agricultural areas that lead to momentary algal bloom and long-term surface water eutrophication (Islam et al., 2022). Many researchers have confirmed that agricultural NPS pollution has become a major contributor to water quality degradation worldwide, making it a great challenge to mitigate associated pollution loads. Therefore, it is of great importance to develop sound strategies, Such as modifying land use structure to create a balance between maximizing agricultural system returns and decreasing associated NPS pollution loads.

Table 2.1: Tabular form of literature review

Author	Quantitative	Economic	Environmental	Social	Water	Land	Intercropping	Uncertainty	Multi-product	Approaches
Mo Lia, (2019)	✓		✓		✓	✓		✓	✓	Optimization-simulation under Uncertainty (Multi-objective non-linear Programming)
Enerlan et al., (2020)	✓	✓					✓	✓	✓	Linear Programming Model
Y.L. Xie (2017)	✓	✓	✓		✓	✓		✓		Stochastic-Fuzzy Optimization, Interval-parameter optimization,
Chongfeng Ren (2018)	✓	✓	✓		✓	✓		✓	✓	Multi-objective Stochastic-Fuzzy programming, Analytical Hierarchy Process
Lina Hao (2017)	✓	✓	✓			✓		✓	✓	Cross-Entropy Method, Spatial Optimization
Najafabadi, Ziaee, and Nikouei (2019)	✓	✓	✓	✓	✓			✓	✓	Multi-objective programming model, Robust Optimization
Li, Fu, Singh, and Tianxiao Li (2020)	✓	✓	✓	✓	✓	✓		✓		Multi-objective non-linear optimization, Fuzzy credibility-constrained programming
Bhatia and Rana (2020b)	✓	✓		✓	✓			✓		Linear Programing Model, Weighted sum model

Table 2.1: Tabular form of literature review (Continued…..)

Marzban Zahra (2021)	✓	✓	✓		✓	✓		✓	✓	Multi-Objective non-linear programming Model
Ramtin Joolaie (2017)	✓	✓	✓	✓				✓	✓	Fuzzy Goal Programming
Tomas Balezentis (2020)	✓	✓	✓	✓				✓		Multi-Criteria Decision Making, SAW, TOPSIS
Nie et al. (2019)	✓	✓	✓	✓		✓			✓	Mix Integer multi-objective non-linear Optimization
Li et al. (2019)	✓	✓		✓	✓	✓		✓	✓	Chance-Constrained Programming (CCP) based multi-objective non-linear programming, Simulation
This Research	✓	✓	✓	✓	✓	✓	✓	✓	✓	**Augmented ε-constraint method with lexicographic optimization**

However, numerous system parts, processes, and elements, in addition to their interrelationships, may be subject to uncertainty. Many system components have spatial and temporal fluctuations, and such information may be displayed as intervals and fuzzy numbers. As a result, while mitigating agricultural NPS pollution through land use adjustment, it is vital to account for many uncertainties in such a complex system. Many modeling approaches have already been utilized in agricultural systems to solve the numerous uncertainties involved with managing and using land issues. TSP has been widely utilized to address agricultural system management issues. It is a useful tool for assisting with medium- to long-term planning issues and may be used to produce cost-efficient management strategies (Jbari et al. 2020). The TSP strategy entails making a first-stage decision prior to the occurrence of a random event, followed by a second-stage decision to minimize "penalties" after the occurrence of the random event. Where a study of policy alternatives is sought, and uncertainties are represented as random variables with established probability distributions, the TSP approach can successfully solve recourse problems. Agricultural NPS pollution loads are erratic due to the influence of stochastic phenomena such as precipitation. As a result, the TSP technique can be used to successfully handle agricultural NPS pollution management under unknown conditions.

The literature discusses the development of user-friendly software for optimal land and water resources allocation and management policies for the Hirakud canal irrigation system in Odisha State, eastern India (Agarwal et al. 2019). The software was designed to meet the needs of surface water, groundwater, and agricultural authorities at the systems level. The model was developed in order to enhance the decision-making ability of the command area concerned. Software development involves the typical phases of software development, including analysis of requirements, detailed specifications, design, programming, testing, and maintenance. The testing and application of the software are said to be very user-friendly.

Sufficient literature contributes to the literature on sustainable agricultural management by offering a tool for decision-makers to better manage land and water resources in a way that is optimal for both the environment and the economy (Tiwari et al. 2020). The use of industrial inputs in agriculture leads to high costs and environmental pollution, causing negative impacts on the economy, human health, and the environment. Developing countries are particularly affected, with cancer incidence on the rise in many of these countries. Studies have shown that agricultural pesticides and fertilizers contribute to the development of cancer. It is, therefore, crucial to study the environmental aspects of agricultural production systems to protect human health. Life cycle assessment (LCA) is an environmental impact assessment methodology used to detect and quantify the energy and materials used and waste generated by crop production, processes, or activities, and its effects on the environment.

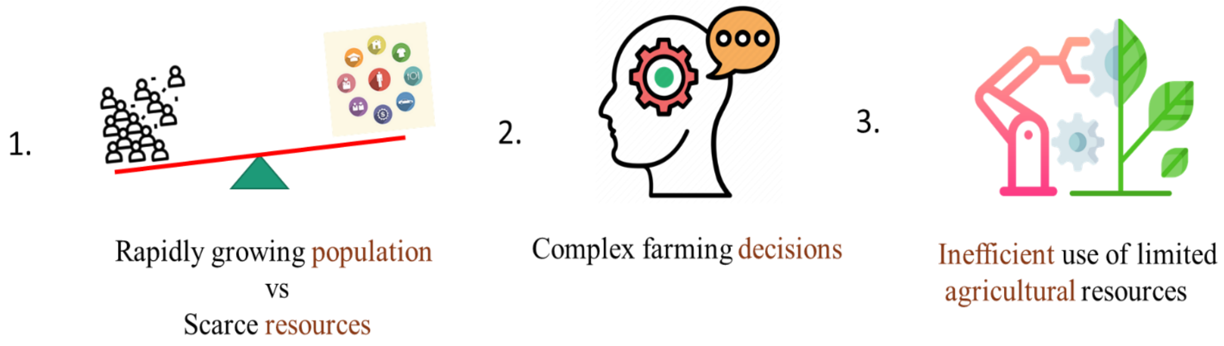
According to recent decades, increased human activities that changed the composition of the earth's atmosphere led to substantial changes in the global climate. Since 1750, there has been a 150%, 40%, and 20% increase in the concentration of greenhouse gases such as methane (CH_4), carbon dioxide (CO_2), and nitrous oxide (N_2O), respectively (Pachauri et al. 2014). The atmospheric CO_2 content had grown to 411.43 ppm in 2019 from 315.98 ppm in 1959. The main source of greenhouse gases in the atmosphere is CO_2, which is followed in importance by methane (16%), nitrous oxide (6%), and fluorinated gases (2%) and is produced by industrial processes and fossil fuels to the tune of 65% and 11%, respectively. The emission varies depending on the area. The continent of North America and Asia each registered total CO_2 emissions of 457 billion metric tons, whereas Europe is the highest emitter of CO_2, with emissions of roughly 514 billion metric tons apiece (Malhi, Kaur, and Kaushik 2021).

Based on the previous discussion a mathematical model consisting of three objective function is presented. Achieving the most desirable objective of profit is considered as highly prioritized with social and food security objectives. The model is focused on sustainable practices in agricultural field and considering worker health conditions. Indeed, number of researchers have studied these three objectives for agriculture improvement. Intercropping practices are considered with in comparison of solo crops in this study. The tools and strategies for decision-making can help businesses in making more informed and sensible choices regarding the crop selection and land allocation. (Ahmed and Sarkar 2019) provided a clear augmented ε-constraint methodology to solve multi-objective mathematical optimization problems for conflicting objectives. In order to demonstrate the value of the suggested strategy, this research also investigates the applicability using a case study.

3. Mathematical Model

In this study, a multi-objective multi-product optimization model has been developed for the agriculture industry. The model considers the total available land for farming for a single time period. Multiple crops are considered and also studied their possible intercropping combination of only two crops at a time in the same field. The mathematical model is based on three objectives, including maximization of profit, ensuring food security by maximizing crop production, and maximization of working opportunities for labor under uncertain crop production. Pakistan is an agriculture-based country, making it rich in its resources; on the other hand illiteracy rate in Pakistan is high that leaving farming workers illiterate and having no analytical skills to fully utilize the agricultural land that they have owned. Just labor, land, and natural inputs do not mean that the agriculture sector can be run efficiently.

3.1 Problem description:



Rapidly growing population
vs
Scarce resources

Complex farming decisions

Inefficient use of limited
agricultural resources

Figure 3.1: Main problems of the research

The rapidly growing population poses problems for almost all sectors, but what it endangers the most is the already scarce resources that we have. If the population keeps growing like this, there will come a time when people will be deprived of the basic necessities required for survival. The purpose of this research is to utilize the limited agricultural resources. Maintain sustainable practices and improve national food security. Most important are land, water, and chemicals. One of the biggest consumers of freshwater is agricultural irrigation, which accounts for over 70% of all annual freshwater withdrawals worldwide (Saccon 2018). Due to the interaction between water and land resources and their direct connection to food security, the ever-increasing food demand brought on by ongoing population growth and socioeconomic development necessitates the optimal use of resources for agricultural production.

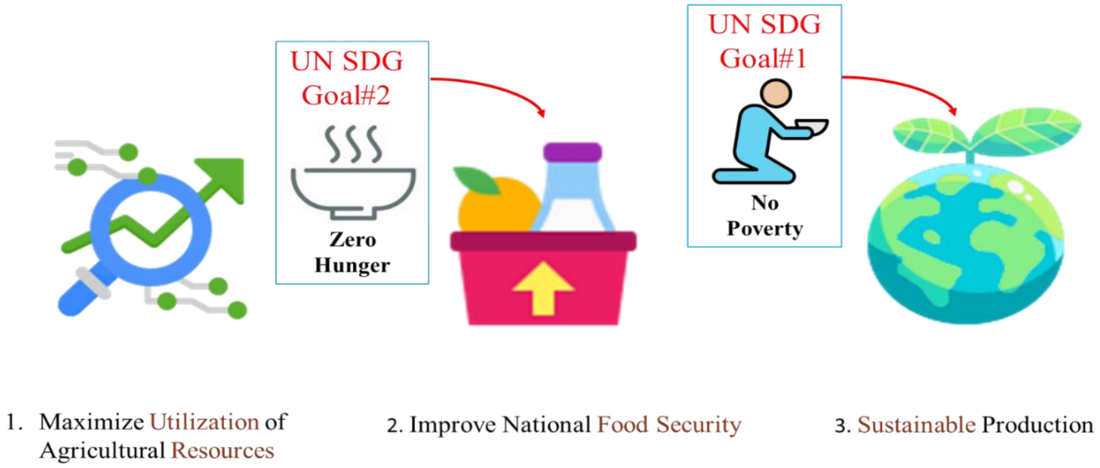


Figure 3.2: Main purposes of the research

The objectives are (1) to closely study the cost and benefits of crops production, (2) exact optimum allocation of land to multiple crops considering the need of the public for food security, (3) to use sustainable activities in the production of crops, (4) maximization of profit for the farmers, (5) creation of jobs while making sure worker safety by considering labor law that allows maximum working hours, (6) optimization of the proposed multi-objective model through Augmented Epsilon Constraint.

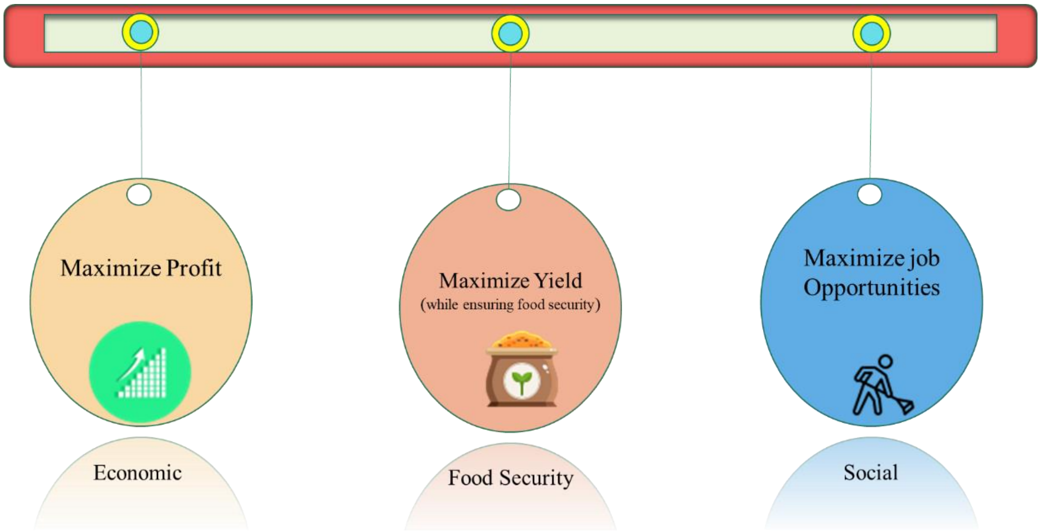


Figure 3.3: Objective functions of mathematical model

3.2 Conceptual framework:

The mathematical optimization model is developed for the main problems and objectives. Considering all facets of research, a conceptual framework is designed for the mathematical model. The conceptual framework shows the dimensions of research and how it will work to achieve the desired objectives. Figure 3.4 shows that the total amount of land is divided into three types on the basis of water availability. And in total, six crops are selected. The total land is subjected to only six selected crops. The percent amount for each type of land is also mentioned, which clearly shows that most of the land is irrigated through surface water.

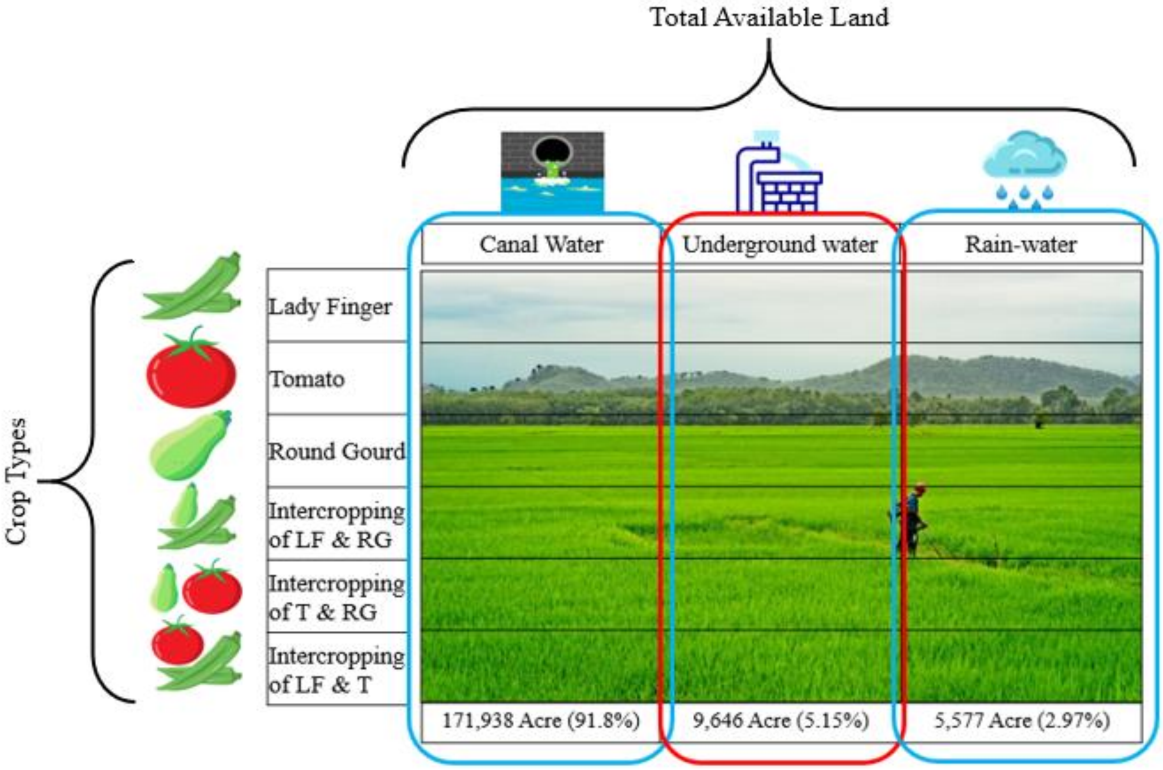


Figure 3.4: Conceptual framework of the research

3.3 Model assumptions:

1. Targeted land is managed under the supervision of one organization
2. Only three crops and their intercropping are selected in the case study
3. Required pesticides, insecticides, labor, water, and fertilizer are available at each location
4. All the required machinery is available
5. The fertility level of the targeted land is constant.
6. The field ground is leveled.

7. Considering water as an input resource.
8. Packaging costs are not considered.
9. Transportation costs of the package from the farm to the local market are constant.
10. 1USD=225PKR

3.4 Notation:

Indices:

The sets for mathematical model formulation are shown in Table 3.

Table 3.1: Sets for the mathematical model

i	Crop types	$i = 1,2,3\ldots I$
j	Agricultural zones	$j = 1,2,3\ldots J$
k	Land Type based on water availability	$k = 1,2,3\ldots K$

Parameters:

The parameters for the mathematical model formulation are shown in Table 4.

Table 3.2: Parameters for the mathematical model

Sym.	Description
s_{ijk}	Selling price of crop *i* at land type *j* in location *k* per kg ($) in local Market
c_{ijk}^{s}	Land Preparation cost of land for crop *i* at land type *j* in location *k* ($/Acre)
c_{ijk}^{se}	Seed cost of crop *i* at land type *j* in location *k* ($/Acre)
l_{ijk}	Required number of worker hours for crop *i* at land type *j* in location *k* (hr/Acre)
c^{l}	Worker wage rate ($/hr)
l^{cap}	Worker maximum working capacity per day (hr)
c_{j}^{sf}	Cost of synthetic fertilizer in location *k* ($/kg)
f_{ijk}^{sf}	Required amount of synthetic fertilizer for crop *i* at land type *j* in location *k* (kg/Acre)
c_{ijk}^{pp}	Plant protection cost (pesticides and insecticides) for crop *i* at land type *j* in location *k* ($/Acre)

c_k^{sw}	Irrigation cost for crop *i* at land type *j* in location *k* ($/Acre-inch)
w_{ijk}	Amount of water required to fully irrigate crop *i* at land type *j* in location *k* (Acre-inch/Acre)
W_k	Total amount of water available in location *k* (Acre-inch)
$\tilde{y}_{ijk}$	Average production rate of crop *i* at land type *j* in location *k* per unit area (kg/Acre)
a_{jk}^{L}	Total available land at land type *j* in location *k* (Acre)
$Alhr_k$	Availability of working hours in location *k* (hr)
f_k^{tsf}	Available amount of synthetic fertilizer at location *k* (kg)
a_k^{hpi}	Available amount of chemicals at in location *k* (kg)
d_{ik}^{F}	Food demand per capita for crop *i* in location *k* (kg/person)
p_k^{T}	Total population of study area in location *k* (person)
γ	Constant for production to population ratio
α	Constant for minimum amount of land to be utilized (%)
c_{ijk}^{tp}	Cost per transported package of crop *i* at land type *j* in location *k* ($)
q^{tp}	Quantity per transported package (kg)
β	Market sales commission (%)

Decision Variables:

The decision variable is the amount of land that should be allocated to different crops *i* in location *j* at land type *k*.

Table 3.3: Decision variables for the mathematical model

x_{ijk}	Amount of land allocated to crop *i* in location *j* at land type *k*

Objective Functions:

- **Maximize profit:**

The optimization model is developed for three objectives, describing the economic and social aspects, and the third one is to ensure food security by maximizing yield. The first objective function in Equation 3.1 is developed that computes the total profit from the whole production zone. The first section of Equation (1) shows the revenue generated by the whole production and is multiplied with β that is the commission fee of the wholesale market and deducted from the farmer as cost. The second section shows the total land preparation cost, the third section computing seed cost, in the fourth section c^l is the worker wage rate $/hr and it shows the total labor cost. In section five, the plant protection cost is shown, including pesticides and insecticides cost, while workers are using to cut extra herbs, not herbicides; thus, the cost is added to labor cost, section six shows the fertilizer cost, and in the seventh section, the irrigation cost is shown. In the last section, the transportation cost per bag from the farm to the wholesale market is added, which is charged by a third party from farmers, and the term $\frac{\tilde{y}_{ijk}}{q^{tp}}$ shows the total amount of bags.

$$\begin{aligned}
\text{Max. Profit } P = {} & \left[\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(s_{ijk} \times \tilde{y}_{ijk} \times x_{ijk}\right)\right] \times (1-\beta) - \left[\left\{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} c_{ijk}^{s} \times x_{ijk}\right\} + \left\{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} c_{ijk}^{se} \times x_{ijk}\right\} \dots\right. \\
& + \left\{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} l_{ijk} \times c^{l} \times x_{ijk}\right\} + \left\{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} c_{ijk}^{pp} \times x_{ijk}\right\} + \left\{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} c_{ijk}^{sf} \times x_{ijk}\right\} \dots \\
& \left. + \left\{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} c_{ijk}^{w} \times x_{ijk}\right\} + \left\{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} c_{ijk}^{tp} \times \frac{\tilde{y}_{ijk}}{q^{tp}} \times x_{ijk}\right\}\right] \qquad (3.1)
\end{aligned}$$

- **Maximize job opportunities:**

The second objective in Equation 3.2 is maximizing labor working opportunities considering human safety practices and labor law. The purpose of this objective is to increase employment locally in a region and help rural development. The jobs that are created is to support all operational activities in the farming of specified zone. The type of operations that help to maximize job opportunities includes land preparation, making beds, fertilizer, pesticides, and insecticides, removing herbs, irrigation, harvesting, and packaging. l_{ijk} represent the required amount of labor hours required for each crop *i*, at land type *j* in zone *k*. l^{cap} shows the maximum amount of working hour that a worker should be allowed to work.

$$\text{Max. Job } l = \frac{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(l_{\mathrm{ijk}} \times x_{\mathrm{ijk}}\right)}{l^{cap}} \qquad (3.2)$$

- **Maximize yield:**

In Equation 3.3, the third objective is formulated to maximize the overall production in order to fulfill food security for the population. This objective is developed to maximize the total output of crops from the total available land of the targeted zone, as maximizing total output leads to the high amount of food available for the public to survive.

$$\text{MaxYield } Y = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \left(x_{ijk} \times \tilde{y}_{ijk} \right) \tag{3.3}$$

Subject to Constraints:

3.4.1 Land availability:

$$\sum_{i=1}^{I} \sum_{j=1}^{J} x_{ijk} \le \sum_{j=1}^{J} a_{jk}^{L} \qquad \forall k \tag{3.4}$$

$$\sum_{i=1}^{I} \sum_{j=1}^{J} x_{ijk} \ge \alpha \sum_{j=1}^{J} a_{jk}^{L} \qquad \forall k \tag{3.5}$$

Equation 3.4 shows that the sum of all allocated land to crop *i*, at land type *j* must not exceed the total sum of available land for each zone *k*. while equation 3.5 ensures the specific amount of land that must be allocated to crops to be utilized. This equation force to use the available land without taking objectives in the consideration.

3.4.2 Labor availability:

$$\sum_{i=1}^{I} \sum_{j=1}^{J} l_{ijk} \times x_{ijk} \le Alhr_{k} \qquad \forall k \tag{3.6}$$

Equation 3.6 shows the summation of required labor hours for each crop at each land type in every zone. It ensures that the number of labor hours required for the total allocation of land to each crop must not exceed the available labor hours at that specific zone of study. Agriculture is labor centric sector that needs a major portion of the labor force. In Agriculture, specifically farming, require more labor force. In Pakistan, the farming practices are mostly on traditional techniques and manual. Advanced machinery is not used, and the reason is farmers do not have more land that requires advanced equipment for efficiency.

3.4.3 Water availability:

$$\sum_{i=1}^{I}\sum_{j=1}^{J} w_{ijk} \times x_{ijk} \leq W_k \qquad \forall k \tag{3.7}$$

Equation 3.7 shows that the total water requirement must not exceed the limit of the available amount of water. It is the summation of water that is needed for each crop to be cultivated at any land type in the selected zone for the whole farming period.

3.4.4 Food security :

$$\sum_{j=1}^{J} x_{ijk} \times \tilde{y}_{ijk} \geq d_{ik}^{F} \times p_k^{T} \times \gamma \quad \forall i,k \tag{3.8}$$

Equation 3.8 ensure the notational food security. It shows that the total amount of production should satisfy the need of people living in that zone. d_{ik}^{F} shows the demand for crop *i* at zone *k* while p_k^{T} shows the total population of zone k. γ is the constant that shows the ratio of production to population for each crop *i*. It removes the limitation of Equation 3.8 in case the demand of population in a specific zone exceeds the production capacity of available land in that zone, then γ reduce the demand proportionally and to balance demand with production.

3.4.5 Fertilizer constraints:

$$\sum_{i=1}^{I}\sum_{j=1}^{J} f_{ijk}^{sf} \times x_{ijk} \leq f_k^{tsf} \qquad \forall k \tag{3.9}$$

Equation 3.9 shows that the total required amount of fertilizer for each crop *i* at available land of zone *k* must be less than the available amount of fertilizer in that zone *k*.

3.4.6 Land allocation/capacity constraints:

$$x_{23k} = 0 \quad \forall k \tag{3.10}$$

$$x_{33k} = 0 \quad \forall k \tag{3.11}$$

$$x_{43k} = 0 \quad \forall k \tag{3.12}$$

$$x_{53k} = 0 \quad \forall k \tag{3.13}$$

$$x_{63k} = 0 \quad \forall k \tag{3.14}$$

The above equations from equation 3.10 to equation 3.14 shows the limitation of different crops at land type. This limitation may be for several reasons; here, the only reason is the limited amount of water availability. Equation 3.10 shows that tomatoes cannot be planted at land type 3 that is irrigated by rainwater, Equation 3.11 shows that round gourd cannot be planted at land type 3, Equation 3.12 shows that the intercropping of ladyfinger and tomato cannot be practice at land type 3, Equation 3.13 shows that the intercropping of tomato and round gourd cannot be practice at land type 3, and Equation 3.14 shows that the intercropping of lady finger and round gourd cannot be practice at land type 3. Thus, these constraint shows tomato, round gourd, and these crops in intercropping are not going to be planted at land type where water is not available in an appropriate amount in the specific time period. The model has been solved through the Augmented ε-constraint method using MATLAB software. The collected data that are used in this research are in Appendix A.

4. Solution Methodology

According to Hwang, M. Masud., (2023) the methods for solving MOMP problems can be categorized into three categories based on the stage in the decision-making process at which the decision maker conveys his or her preferences: There are generally three types of methods: a priori methods, interactive methods, and a posteriori method. A priori approaches involve the decision maker expressing his or her preferences prior to the solution process (e.g., assigning goals or weighting to the objective functions). The critique raised about a priori approaches is that it is extremely difficult for the researcher to know ahead of time and precisely quantify (through goals or weights) their preferences. In interactive approaches, phases of interaction with the decision maker are alternated by stages of the computation; thus, the entire procedure usually converges to the most favored option after a few iterations.

The decision maker gradually steers the search toward the most desirable choice. The disadvantage is that he or she cannot see the entire image (the Pareto set) or even an approximation of it. As a result, the most favored answer is "most preferred" in regard to what he or she has observed and compared thus far. The a posteriori method generates efficient solutions for the query (all of them or a suitable representation) and then involves the decision maker in order to decide on the most desired one among them. Because of the computing work required, generating methods are the least common. The weighting method and the ε-constraint approach are the most commonly utilized generating methods. For this context, we suggest employing the augmented ε-constraint technique (AUGMECON), a novel form of the standard ε-constraint approach that addresses its well-known flaws.

4.1 Advantages of ε-constraint method over weighting method:

The e-constraint approach has some advantages over the weighting approach (Mavrotas 2009).

i. In the case of linear modeling, the weighting approach applies to the initial viable region, creating a corner solution (extreme solution), resulting in only the most effective solutions. The e-constraint technique, on the other hand, modifies the original feasible zone and can create non-extremely efficient solutions. As a result, with the weighting approach, we may spend plenty of time running redundant runs because there can be a number of weight combinations that end up resulting in the same efficient solution. With the e-constraint, on the other hand, we can utilize practically every iteration to produce a distinct efficient solution, resulting in a more comprehensive depiction of the optimal set.

ii. In multi-objective integer programming models and mixed integer programming problems, the weighting technique cannot yield truly efficient solutions, whereas the e-constraint method is exempt of this limitation.

iii. The scaling of the desired objective functions has a substantial influence on the achieved outcomes in the weighting approach. As a result, before calculating the weighted total, we must scale the desired objective functions to a common scale. This is not required in the e-constrained technique.

iv. The ε-constraint method also has the advantage of allowing us to manage the number of created efficient solutions by properly altering the amount of grid points in the range of each objective function. This is more difficult using the weighting approach.

The early departure from the nested loop when the issue becomes infeasible is a unique addition to the algorithm that greatly accelerates the procedure in the case of multiple (more than three) desired objective functions. Starting with a more flexible form of the constrained goal functions, the algorithm gradually tightens the constraints. This indicates that for the maximization of objective functions, the RHS of the relevant constraint is increased progressively from the minimum (opposite for the minimization of objective functions). When a problem becomes infeasible in this procedure, it signifies that further restricting the relevant objective function will result in infeasible solutions. As a result, the algorithm exits the innermost loop and continues with the prior objective function's next waiting grid point, which corresponds to the outer loop. The complete algorithm Augmented ε-constraint method is shown in figure 3.

4.2 Steps of ε-constraint method AUGMECON:

The following are the main steps involves in ε-constraint method.

1st Step

Develop a Multi-Objective Optimization Problem “P”

$$
\begin{aligned}
Z1 &= \max / \min (f1\,(x)) \\
Z2 &= \max / \min (f2\,(x)) \\
&\;\;. \\
&\;\;. \\
Zn &= \max / \min (fn\,(x)) \\
&\text{s.t: } x \in S
\end{aligned}
$$

2^{nd} Step

Set the priorities to the Objectives

After developing a multi-objective mode, next step is to set priorities. Priorities of the Objectives must be specified and ordered at the very start. Assures that the units for each objective function are exactly the same. Following these procedures, the model should be transformed from a single objective function P to a multi-objective model P' using the Augmented ε-constraint approach. According to the proposed method, the highest priority objective function should be considered as an objective function, while the other objective functions will be subject to constraint with all other constraints. At this stage, the second and third objective functions will come into constraint and will in in inequality constraint having right hand side with a fix value that is symbolized by the symbol ε. And the value for ε can be calculated using the payoff table.

3^{rd} Step

Transform Problem P into P´ by Augmented ε-constraint method

- Suppose we have multi-objective function as

$$\max / \min \quad (f1\ (x), f2\ (x), f3\ (x) \ldots fn\ (x))$$
$$\text{s.t: } x \in S$$

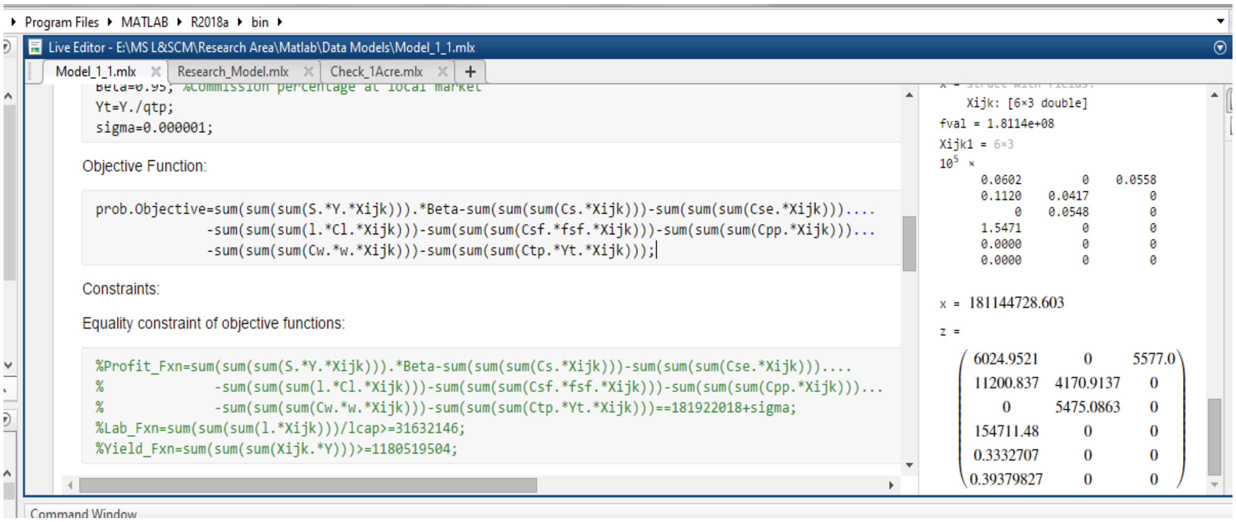
- Transform the problem P into P'

$$\max / \min \quad f1\ (x)$$
$$\begin{aligned} \text{s.t: } f2\ (x) &\leq \varepsilon 1 \quad \text{for min function} \\ f3\ (x) &\geq \varepsilon 2 \quad \text{for max function} \\ &. \\ &. \\ fn\ (x) &\geq \varepsilon n\text{-}1 \\ \text{and other constraints} & \end{aligned}$$

4^{th} Step

Calculate ranges of ε1 and ε2 by payoff table

Payoff table need to be constructed using lexicographic optimization. Calculating the values of ε1 and ε2 first we have to construct payoff table. Explaining the construction of payoff table, first we have to organize the table in from-to chart design. The objective functions will come in column while the problems are in the row. Starting with the first problem, need to solve the mathematical optimization model for highly prioritized objective function as a single objective model only. At this stage we ignore other objective functions so that the result of only one objective is computed as shown in figure 4.1.



```
Beta=0.95; %commission percentage at local market
Yt=Y./qtp;
sigma=0.000001;
```

Objective Function:

```
prob.Objective=sum(sum(sum(S.*Y.*Xijk))).*Beta-sum(sum(sum(Cs.*Xijk)))-sum(sum(sum(Cse.*Xijk)))....
               -sum(sum(sum(l.*Cl.*Xijk)))-sum(sum(sum(Csf.*fsf.*Xijk)))-sum(sum(sum(Cpp.*Xijk)))...
               -sum(sum(sum(Cw.*w.*Xijk)))-sum(sum(sum(Ctp.*Yt.*Xijk)));
```

Constraints:

Equality constraint of objective functions:

```
%Profit_Fxn=sum(sum(sum(S.*Y.*Xijk))).*Beta-sum(sum(sum(Cs.*Xijk)))-sum(sum(sum(Cse.*Xijk)))....
%               -sum(sum(sum(l.*Cl.*Xijk)))-sum(sum(sum(Csf.*fsf.*Xijk)))-sum(sum(sum(Cpp.*Xijk)))...
%               -sum(sum(sum(Cw.*w.*Xijk)))-sum(sum(sum(Ctp.*Yt.*Xijk)))==181922018+sigma;
%Lab_Fxn=sum(sum(sum(l.*Xijk)))/lcap>=31632146;
%Yield_Fxn=sum(sum(sum(Xijk.*Y)))>=1180519504;
```

```
x = struct with fields:
    Xijk: [6×3 double]
fval = 1.8114e+08
Xijk1 = 6×3
10^5 ×
      0.0602         0    0.0558
      0.1120    0.0417         0
           0    0.0548         0
      1.5471         0         0
      0.0000         0         0
      0.0000         0         0

x = 181144728.603

z =
```

$$\begin{pmatrix} 6024.9521 & 0 & 5577.0 \\ 11200.837 & 4170.9137 & 0 \\ 0 & 5475.0863 & 0 \\ 154711.48 & 0 & 0 \\ 0.3332707 & 0 & 0 \\ 0.39379827 & 0 & 0 \end{pmatrix}$$

Figure 4.1: Solution of the single objective mathematical model in MATLAB

Table 4.1: Construction of payoff table using lexicographic optimization (first problem)

	1st Priority Objective	2nd Priority Objective	3rd Priority Objective
1st Problem	Max/Min 1st Objective (e.g., TP) s.t (all constraint) calculate: (u*, x*, z*) f_1^1= TP (u*, x*, z*)	f_2^1= TJ (u*, x*, z*)	f_3^1= TY (u*, x*, z*)

The resultant value of the model will come in row first and column first. And we know the highly prioritized objective function is the economic objective to maximize the overall profit of production. After that, the same mathematical model will be solved for the second highly prioritized objective function, and the resulting value will come to row first and column second. The second objective function of the model is the social objective, maximizing working opportunities. In the same way, the optimization model will be solved for the third objective function of the model. The value of the third objective function will come to row first, column third, as shown in Table 4.1. This model has only three objective functions, and the last objective function is to maximize overall production.

The second problem will be solved for each objective function but with the consideration of resulted values of the first problem. Solving problem second problem first go for the second highly prioritized objective function. Like in this case, solving the second problem need to consider the second highly prioritized function (social) first and add the resulting value of the highly prioritized objective function solved for the first problem as an equality constraint and add some allowable tolerance ranges from 10^{-6} to 10^{-3} with all other constraints. The resulting value will be added to row two, column two, as shown in Table 4.2. Now consider the value of the second problem for the second objective function as an equality constraint and solve for the first highly prioritized objective function (economic) and third objective function separately.

Table 4.2: Construction of payoff table using lexicographic optimization (second problem)

	1st Priority Objective	2nd Priority Objective	3rd Priority Objective
1st Problem	Max/Min 1st Objective (e.g., TP) s.t (all constraint) calculate: (u*, x*, z*) f_1^1= TP (u*, x*, z*)	f_2^1= TJ (u*, x*, z*)	f_3^1= TY (u*, x*, z*)
2nd Problem	f_1^1= TP (u", x", z")	Max/Min 1st Objective TP= $f_1^1+\delta_1$ s.t (all constraint) calculate: (u", x", z") f_1^1= TP (u", x", z")	f_3^2= TY (u", x", z")

The procedure to construct the payoff table remains the same and moving on to the third problem solution. Now first we have to solve the mathematical model for the third objective function. Solving the model for the third objective function need to consider the values of two highly prioritized objective function solved in problem two as an equality constraint and will be added some allowable tolerance value that has a range of 10^{-6} to 10^{-3}. The first resulting value of the third problem will come to row three and column three, as shown in Table 4.3. Now solving the third problem for the remaining two objective functions and considering the resulting value of the third objective function in problem three as an equality constraint along with other constraints and solving the model. The result will be added to row three, column one, and the same procedure will be followed for the second objective function.

Table 4.3: Construction of payoff table using lexicographic optimization

	1st Priority Objective	2nd Priority Objective	3rd Priority Objective
1st Problem	Max/Min 1st Objective (e.g., TP) s.t (all constraint) calculate: (u*, x*, z*) f_1^1= TP (u*, x*, z*)	f_2^1= TJ (u*, x*, z*)	f_3^1= TY (u*, x*, z*)
2nd Problem	f_1^1= TP (u”, x”, z”)	Max/Min 1st Objective TP= $f_1^1+\delta_1$ s.t (all constraint) calculate: (u”, x”, z”) f_1^1= TP (u”, x”, z”)	f_3^2= TY (u”, x”, z”)
3rd Problem	f_1^3= TP (u’, x’, z’)	f_2^3= TJ (u’, x’, z)	Max/Min 1st Objective TP= $f_1^2+\delta_1$ TJ= $f_2^2+\delta_2$ s.t (all constraint) calculate: (u’, x’, z’) f_3^3= TP (u’, x’, z’)

As we have three objective functions in the model, in case objectives are more than three still, the procedure will be the same to construct the payoff table. First problem is solving as a single objective for each objective function. After solving the model for each objective function separately along with all constrain and record the results, we now have to proceed to the second problem. In the second problem, first we solve for second objective function keeping the resulted value of high prioritize objective function value as an equality constraint along with other constraints. And then using the updated value of the second objective function as a quality constraint and solving the model for other objective functions. The same procedure will be used for the third problem. Where first, we will solve the third highly prioritized objective while keeping the updated values of the first two objective functions as an equality constraint along with other constraints.

Innovations have had a significant role in the process of economic growth. The development of technology has a significant impact on rising incomes and increased productivity. This may be observed in agriculture, where growth in the global population has boosted food consumption and sparked a desire for innovations to boost food production and meet the world's expanding population (Chavas and Nauges 2020). Farmers often maximize the present value of discounted future revenues, according to the majority of economic models reflecting farmers' decision-making process to embrace (or not) a new technology. Risk and information acquisition via learning are two key factors that enter this decision-making process since there is typically a great deal of ambiguity around new agricultural technology. Farmers are frequently thought of as Bayesian learners who learn from their own and other farmers' experiences.

Innovations are characterized by uncertainty, particularly in the context of agriculture, where factors such as the farmer's human capital and the local agronomic and climatic variables determine the applicability and significance of new technology for a certain farm (Huffman 2020). The optimum way to apply the technology could also be unclear, especially if it is combined with other production elements such as fertilizers. In this situation, farming expertise and human talents may also be important. These elements make the farmer's potential future income unclear. Future pricing is also likely to be unpredictable, particularly how decisions concerning widespread adoption may affect prices (Chavas and Nauges 2020).

Farming is a risky profession because unexpected weather changes and insect damage may have significant impacts on crop production (Chavas 2018). Farmers pay attention to the variability in returns variance and higher moments of the distribution as well as the expected return, the mean or first moment of the distribution of returns generated by the new technology, since it has been established that farmers are sensitive to risk. In dealing with uncertainty, several techniques are implemented to better estimate the exact future value based on past information (Ward and Singh 2015). The most common techniques are the use of statistical tools. Distributions are efficient tools for the measurement of uncertainties.

The parameter of the average production rate is taken as uncertain. The data for the last decade is taken for each crop and applied a distribution fitter tool using MATLAB software. Using different distributions for the data of each crop production and finding the best distribution fit for the data. After applying several distributions to the data, a single distribution is selected for each crop data to compute an exact estimate of future production. The criteria for selection best distribution for data are based on the likelihood value. The distribution having a maximum log-likelihood value is considered as best distribution (Ghamghami and Beiranvand 2022). After the selection of the best distribution, a deterministic value is computed and added to the model to solve.

4.3 Analytical computation:

The data for most of the parameters were put as such it was collected from primary and secondary sources. There are several parameters that require analytical calculations to fit the data for the model. As the crops are selected, and for the model, the value of each parameter for every crop needs to be a single value that is assigned and represents that specific crop value completely. For example, consider a single crop, “tomato”. The parameter s_{ijk} shows the selling price ($) of tomato, and this is a single value in any case. But if we consider the intercropping of tomato with ladyfinger. Then a single value from primary or secondary data is not available that represents both crops selling prices by a single value.

The reason for this contradiction is the different prices of crops in the market. It may be the same for some time but not always. It is not just a selling price at the market, but there are a few other parameters in the model that are in direct contact with price computation, like production. Now the production of each crop per acre is different, so again, the same issue comes to mind how a single value can represent both at the same time. That’s why before using the main methodology for the mathematical model need these calculations.

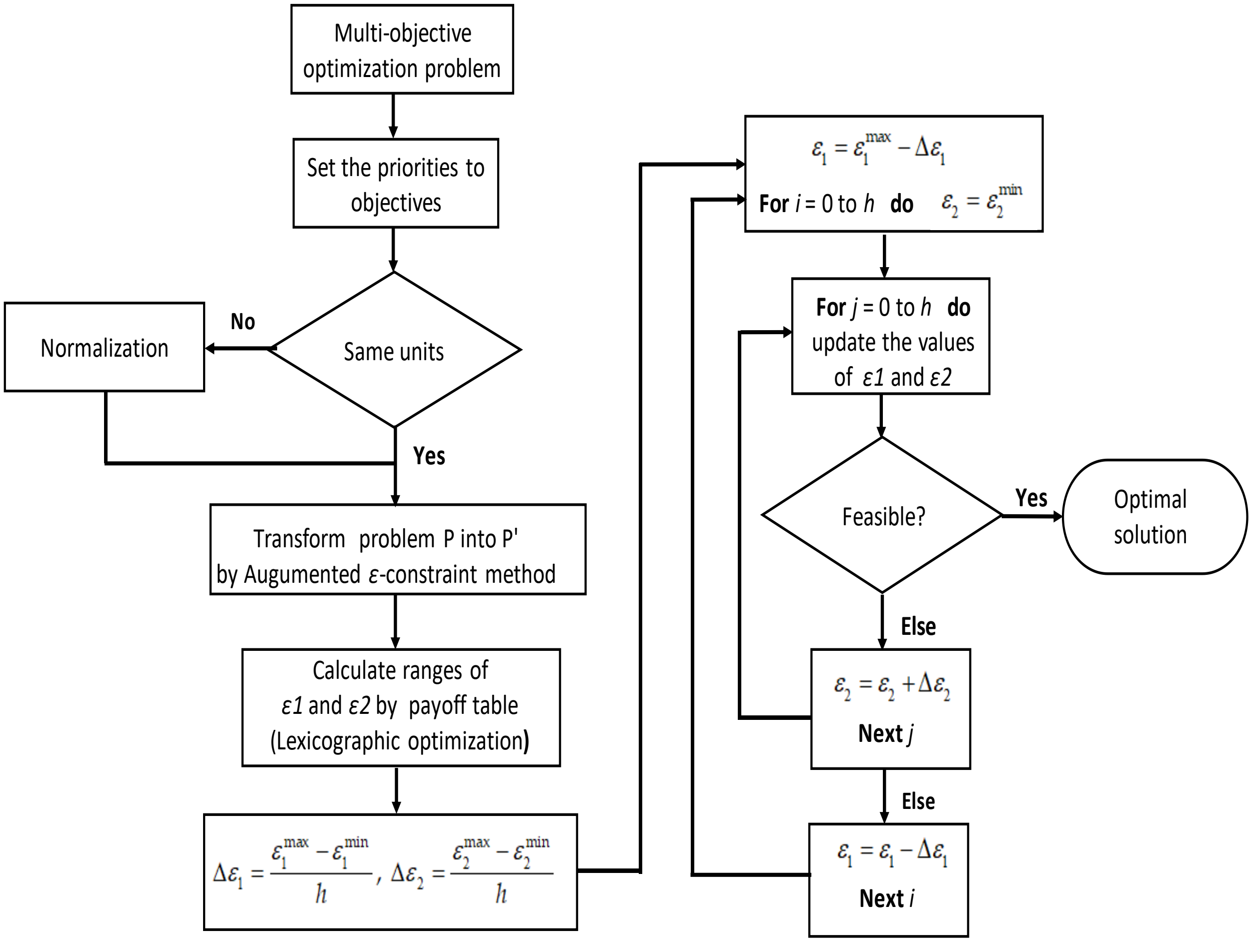


Figure 4.2: Solution algorithm of augmented ε-constraint method (Ahmed and Sarkar 2019)

The parameter value except selling price per kg and average production rate per acre for intercropped crops are simply added. First, we need to compute the average production rate for intercropped. For example, we have two crops c_1 and c_2 . The average production rate for intercropping of c_1 and c_2 computed as:

$$\text{Average production of intercropped} = \sum_{i=1}^{I}\left\{(production of\ c_i)\times(1-r_i)\right\} \qquad (4.1)$$

Where r_i shows the amount (%) decreased in the production of each crop due to the intercropping practice, as the other crop also occupy land. Where production of c_i exact production of crop *i*. Thus, the production from intercropping of two crops can be expressed as:

$$y_{12} = c_1(1-r_1) + c_2(1-r_2) \qquad (4.2)$$

Considering an example of intercropping of ladyfinger with tomato. From data source the production of ladyfinger per acre (c_1) is 2829 kg while the average production of tomato per acre (c_2) is 3470 kg. when ladyfinger come in intercropping with tomato, the production lady finger reduced by 25% and the total amount of ladyfinger contribution will be 2829 x (0.75) while the production of tomato in intercropping with ladyfinger is decreased by only 5% and the amount of tomato contribution in overall intercropped production will be 3470 x (0.95). Using the data in the equation 4.2:

$$y_{12} = 2829(1-0.25)+3470(1-0.05) \tag{4.3}$$

$$y_{12} = 2122+3296 \tag{4.4}$$

$$y_{12} = 5418$$

Thus, a single value is computed, and this value is now representing the overall production for intercropping of ladyfinger with tomato, considering the exact production of each crop that is produced with the combination. The same computation is taken for the remaining crops that are in intercropping combination. Thus, by this approach, intercropping is added as a single entity to the main optimization model.

The analytical computation for the next parameter is discussed now. The next parameter that requires pre-calculation before adding to the main model is the selling price. It is quite clear that the selling price of any crop is a single value that completely represents that specific crop value. However, in the case of intercropping, this is not applicable to consider the selling price of one crop as it is not representing another crop value and is not a realistic value for exact calculation.

For the parameter of yield per acre, we consider the percent reduction in production of a specific crop by the intercropping practice. Here for the selling price, we have considered the percent contribution of each crop to the overall production of the intercropped entity. For example, two crops are in intercropping. One has a contribution of 40% to overall production, and another has 60% to overall production achieved by intercropping. The same percentage will be multiplied by the respective selling price of each crop.

Now considering equation 4.4, which shows the amount of production contribution of each crop to the overall production. The equation depicts that the production of ladyfinger in intercropping with tomato per unit acre of land is 2122kg while the production rate of tomato in intercropping with ladyfinger per one acre of land is 3296kg. Now to find out the combined price value that is a single value and representing both crops exactly the same in intercropping. Thus, the equation can be written as:

$$\text{Contribution of each crop c.c}_i\,(\%) = \frac{amount\ of\ yield\ per\ acre\ for\ c_i\ (kg)}{total\ amount\ of\ intercropping\ (kg)} \times 100 \qquad (4.5)$$

$$\text{Price} = \sum_{i=1}^{I} (selling\ price\ of\ c_i \times c.c_i) \qquad (4.6)$$

Considering the price of ladyfinger equal to Rs.59 and tomato selling price is Rs.69. Finding out the contribution of each crop in percent amount we need yield of each crop per acre of land in sole sowing and the total amount of production in intercropping that is already calculated in equation 4.4. Calculating the percent contribution for each crop in intercropping combination, we have to use equation 4.5 :

$$\text{Contribution of ladyfinger (\%)} = \frac{2122}{5418} \times 100$$

$$= 39.1\ \% \qquad (4.7)$$

$$\text{Contribution of tomato (\%)} = \frac{3296}{5418} \times 100$$

$$= 60.9\ \% \qquad (4.8)$$

Now putting the selling price value of each crop and their percentage contribution to overall production of intercropping in equation 4.6 :

$$\text{Price} = (59 \times 0.391) + (69 \times 0.609)$$

$$\text{Price} = 65\ \text{PKR}$$

This is a combined representation of selling price of intercropping of ladyfinger with tomato.

5. Results and Discussion

The developed multi-product and multi-objective model for the optimization of crops with three objectives, including profit, jobs creation, and production with uncertain yield of crops consideration, was solved through MATLAB, and optimization was performed through the Augmented ε-constraint method. The model was solved for only one zone, and the selected zone is Peshawar, district of Khyber Pakhtun Khwa province, Pakistan, shown in Figure 5.1. Total land is categorized into three sections. The first type is that land which is irrigated by canal or surface water and rainwater, the second type of land is irrigated by underground water and rainwater while the third type of land is irrigated through rainwater only. For cost calculation, major costs that are considered are land preparation cost, seed cost, fertilizer cost, bed making, irrigation cost, plant protection cost including pesticides and insecticides cost only, labor cost, and transportation cost from farm to domestic wholesale market. This study only focused on six crops that are three vegetables, and the intercropping of two on the same farm at the time.

5.1 Main crops:

There are six crops (*i*) selected in total in this study. The selected crops are lady finger, tomato, round gourd, intercropping of lady finger with round gourd, intercropping of tomato with round gourd and intercropping of lady finger with tomato. Table 5.1 shows number of crops selected.

Table 5.1: List of selected crops

Notation for Crops (*i*)	Description
i=1	Lady Finger
i=2	Tomato
i=3	Round Gourd
i=4	Intercropping of Lady Finger and Round Gourd
i=5	Intercropping of Tomato and Round gourd
i=6	Intercropping of Lady Finger and Tomato

5.2 Land types:

The total amount of land that is considered for this research of the selected zone is classified into three categories on the basis of water availability. The first type of land is the one having high proportion is canal land type. This land type is irrigated through land water or surface water. It means that there is a proper network of water management and easy access. And rainwater is also included with canal water. The second type of land is underground land, and this land is irrigated through underground water, including tube wells, wells, etc., and also rainwater. While the last one is rainwater land that is irrigated through rainwater only. Table 5.2 has listed all types of land.

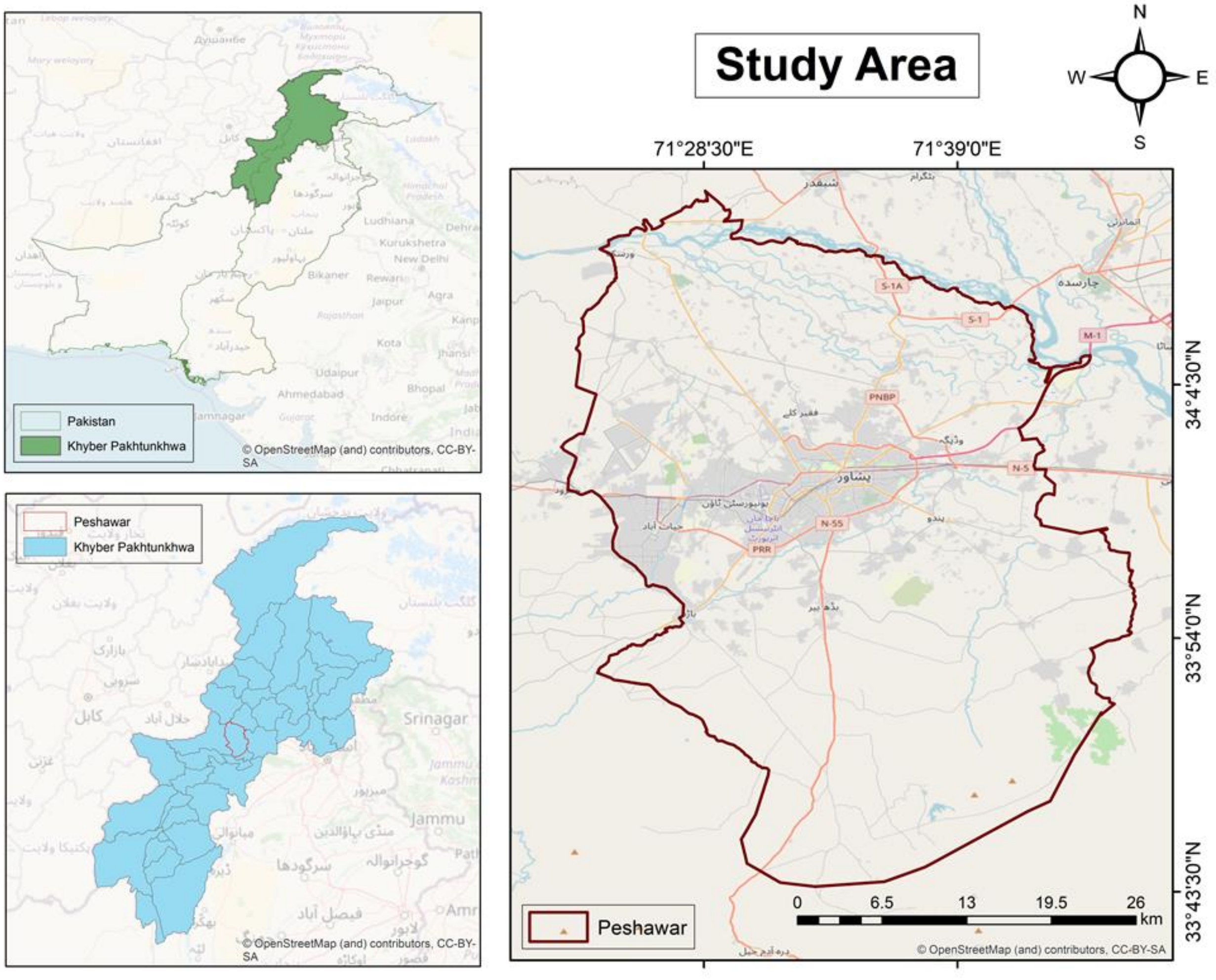


Figure 5.1: Map of the selected zone of study

Table 5.2: Types of land

Notation for Land Types (*j*)	Description
j=1	Types of land that is irrigating through Canal water (surface water, , rivers etc.,)
j=2	Type of Land that is irrigating through underground water (tube well etc.,)
j=3	Type of land that is just irrigating through rainwater

5.3 Optimal results of the model:

Solving the multi-objective multi-product optimization model using MATLAB tool gives optimal results with crop selection and land allocation at the targeted zone of the study. Table 5.3 shows the value of profit (economic objective), and the value is 181,144,729 ($). This computed value is the sum of profit obtained by all types of crops at the total amount of land in the selected zone. No. Of working opportunities (social) and yield objectives at the optimal point. Optimally allocating the total amount of land to the selected crops gives working opportunities, and all those opportunities summing up gives a total number of working days, and the value is 31,632,146 (days). The land that is allocated to different crops at different land type gives a different type of vegetable, and the summation of all crops production at the total amount of land provide the total yield and the value is given in Table 5.3, and that is 1,180,519,505 (ton).

Table 5.3: Optimum values of objective functions

Profit ($)	No. of Working Opportunities (Days)	Yield (ton)
181,144,729	31,632,146	1,180,519,505

5.4 Crop selection and allocation:

The main goal of this optimization model was to provide optimum results with multiple objectives and several constraints. Obtaining optimum results consequently leads us to the best selection of crops and allocation of crops to the available land. The computed crop selection and land allocation are shown in Table 5.4. The optimal allocation of land to crops in the table shows that 6,025 acres of land is allocated to ladyfinger at land type 1 (canal water), and 5,577 acres of land is allocated at land type 3 (rainwater). For tomatoes, 11,200 acres of land is allocated at canal water land, while

4,171 acres of land is allocated at underground water land. Five thousand four hundred seventy-five acres of land are allocated to a round gourd at underground water land. As it is observed that tomato and round gourd need less amount of water compared to ladyfinger. And the cost of irrigation is high for underground water in comparison to canal water. Thus, the model has allocated underground water land to tomato and round gourd in order to minimize total cost.

Table 5.4 shows that the highest amount of land is allocated to intercropping of lady finger and round gourd. The amount of land that is allocated is 154,712 acres of canal water land. As the irrigation cost of canal water is far less than underground water and at rainwater land, the intercropping of ladyfinger and round gourd is not possible because of round gourd that's why a high percentage of land allocated at canal water land. The results show that there is zero allocation of land to the intercropping of ladyfinger with tomato and intercropping of tomato with round gourd.

Table 5.4: Amount of land allocation to crop i, at land type j in location k (Acre)

Crops/Land Type	Canal Water	Underground Water	Rainwater
Lady Finger	6025	0	5577
Tomato	11200	4171	0
Round Gourd	0	5475	0
Intercropping of Lady Finger and Round Gourd	154712	0	0
Intercropping of Tomato and Round gourd	0	0	0
Intercropping of Lady Finger and Tomato	0	0	0

From Figure 5.2, we can clearly understand the allocation of land to different crops at each land type. Here it is quite clear that most of the land portion is allocated to Intercropping of ladyfinger with a round gourd, and the available land of the first land type that is irrigated through canal water is high. Therefore, a high amount of land is allocated to canal water land for the best-resulting crop.

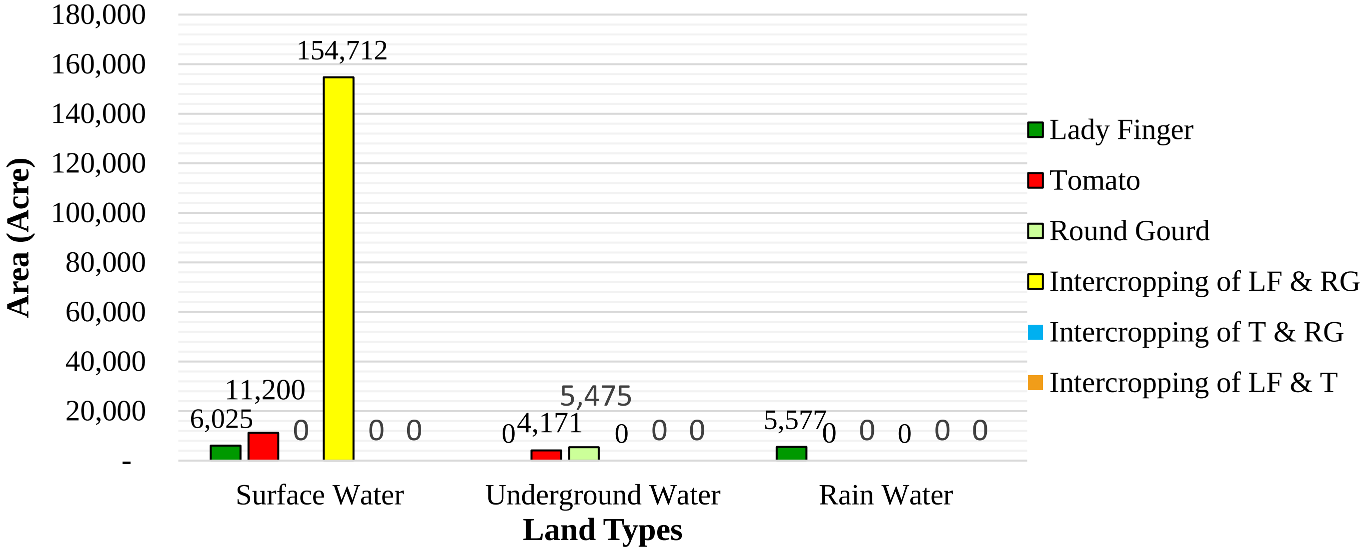


Figure 5.2: Area allocation to each crop at each location

5.5 Types of cost:

It is discussed that the model is multi-objective. And the prior objective is to maximize the profit. Maximizing the profit will consequently minimize the total cost. Different types of costs are associated with farming activities and operations. For this model, we have categorized costs into seven types. Packaging cost is excluded from the computation. Several types of costs incurred in the production of crops are listed in Table 5.5.

Table 5.5: Different types of cost

S. No.	Types of Cost
1	Labor cost
2	Land preparation cost
3	Seed cost
4	Irrigation
5	Fertilizer cost
6	Plant Protection cost
7	Transportation cost (Farm to Market)

Figure 5.3 show the types of cost and the percentage contribution of each type to the overall cost of production of the total land in the selected zone as per the optimal solution. From these results, we observe that labor cost is the main cost that contributes to 53% of the total cost, as it is quite clear that the whole agriculture sector is labor centric. And especially farming is based on labor skills and frequently needs labor from start to end. Fertilizer plays a crucial role in the quality production of crops. This cost may vary location by location and depends on the fertility of the selected land. If the land is fertile so the need for fertilizer will be less, and thus the cost will be low. Here the contribution of fertilizer cost is 15% of the total cost.

There are several methods of farming, and bed designs may be different. There are variations in seed cost, and it completely depends on the type of seeds and seed sowing distance. From the result, it is observed that the contribution of seed cost to total cost is 14%. Crops face different pest attacks in specific areas; also, insects affect the plants and fruit of plants. These attacks and situations depend on several factors; more prominent are the climate and natural conditions of that zone (Schneider, Rebetez, and Rasmann 2022), (Bajwa et al. 2020). Cost of pesticides and insecticides are combinedly considered as plant protection cost, and its contribution to the overall cost is 8%.

The transportation cost of the product from one point to another is considered one of the major costs mostly. Transportation cost depends on distance, weight, and volume. The considered transportation cost is from the farm to the near wholesale market, and it contributes 8% to the total cost value. After harvesting one crop, the land needs to be prepared for another crop, and this land preparation cost is 3% of the total cost. High consumption of water is in Irrigation, as canal water cost is too low compared to underground water and the land to canal water is more than underground water. Thus, the irrigation cost is low enough in this zone and contributes to approximately 1% of the total cost.

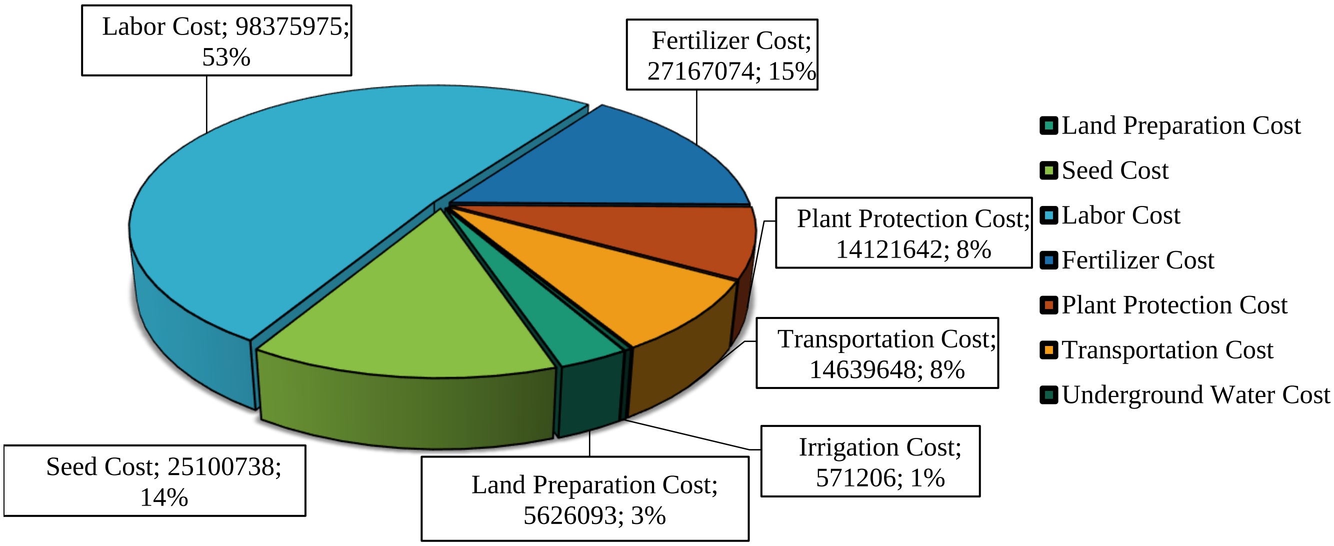


Figure 5.3: Types of cost contribution to overall cost of production

5.6 Computation of crops per acre area:

The optimal results are discussed, which provide the overall and high-scale output of crops to each objective and the costs that are contributing. After solving the model and deeply studying the results, we observed the effect of each crop on each objective. The optimum point does not provide the low-scale insight that is incorporated into high-scale results. Consider the scale of one acre of land and make computation in order to get the effect of each crop on each objective function in the model. This low-scale computation has been done only for canal water land as it contributes 91.8% to total land.

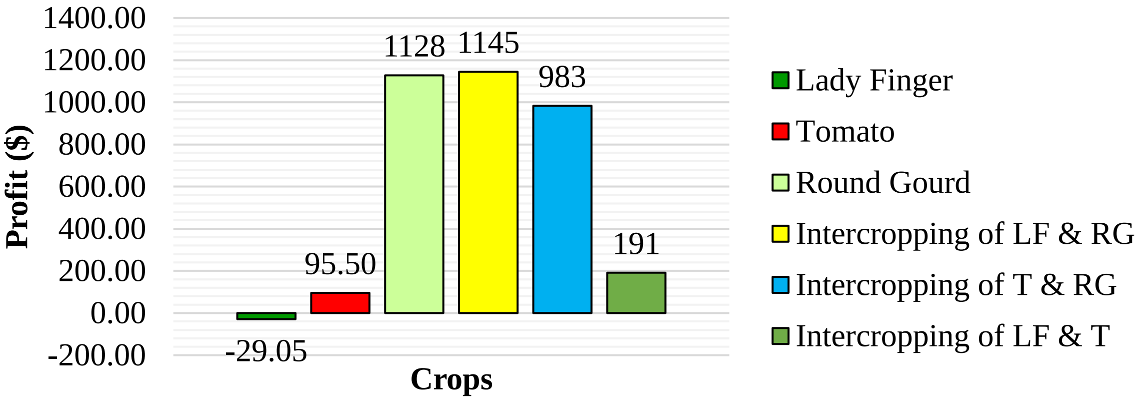


Figure 5.4: Profit of crop i per acre ($)

The profit of each crop per acre of land is given in Figure 5.4. From this figure, it has been depicted that not all the crops give profit. This figure shows a high variation of profit among the crops at the same land type in the same zone. Intercropping of ladyfinger with round gourd shows a high amount of profit among all, and the value is $1145. While round gourd shows a second high amount of profit per acre, and its value is $1125. The profit difference of intercropping of ladyfinger to round gourd is a little higher than solo round gourd. Furthermore, the intercropping of tomato with round gourd per acre of land shows a profit of $983. Among all three combinations of intercropping, the low amount of profit is from the intercropping of ladyfinger with tomato, and its value is $191. Solo tomato crops give $95.5 of profit, while the interesting point in this bar chart is it shows that solo lady finger is not giving any profit but loss. As the labor cost is high and the selling price is low, the loss is $29 per acre.

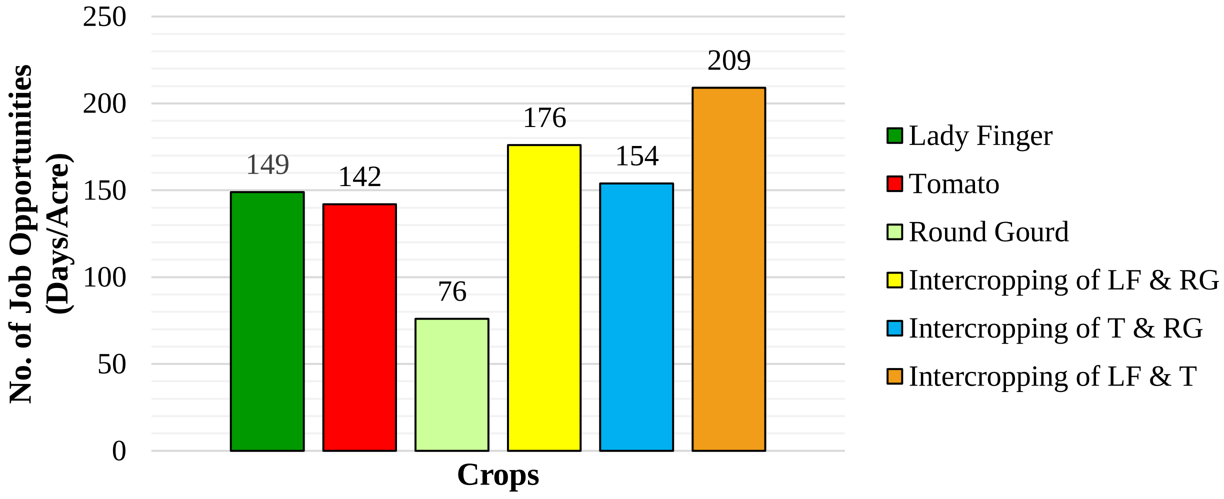


Figure 5.5: Number of working days created by crop i per Acre

The second objective function of the model was to maximize job opportunities. Figure 5.5 shows the number of working days that are required for each crop per acre of land. Thus, the intercropping of ladyfinger with tomato requires a high amount of working days, and the value is 209 days, followed by intercropping of lady finger with round gourd, and it requires 176 days of labor. Intercropping of tomato with round gourd requires less amount of working days compared with the remaining intercropping combinations. It needs 154 working days per acre of land. In solo crops, the ladyfinger requires 149 working days, which is a high vale, while the tomato crop needs 142 working days, and the round gourd requires the least amount of working days of 76.

The third objective of this study was to ensure food security. And the function was to maximize overall food production. Figure 5.6 depicts that the intercropping of lady finger and round gourd has the highest production rate and gives 6,935 kg of food per acre. While the intercropping of tomato and round gourd yields 6,402 kg per acre and intercropping of ladyfinger and tomato produces 5,418 kg of food per acre. On the other hand, round gourd per acre produces 5,066 kg is the highest among selected solo crops, followed by tomato, which has a production of 3,470 kg/acre. The least amount of production is of ladyfinger, which is 2,829 kg in the selected zone.

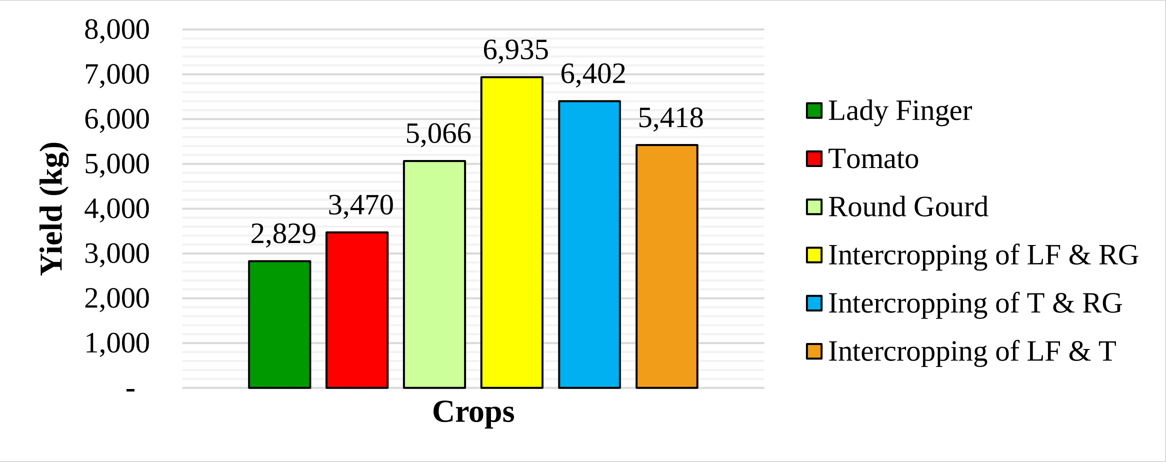


Figure 5.6: Yield of crop i per acre (kg)

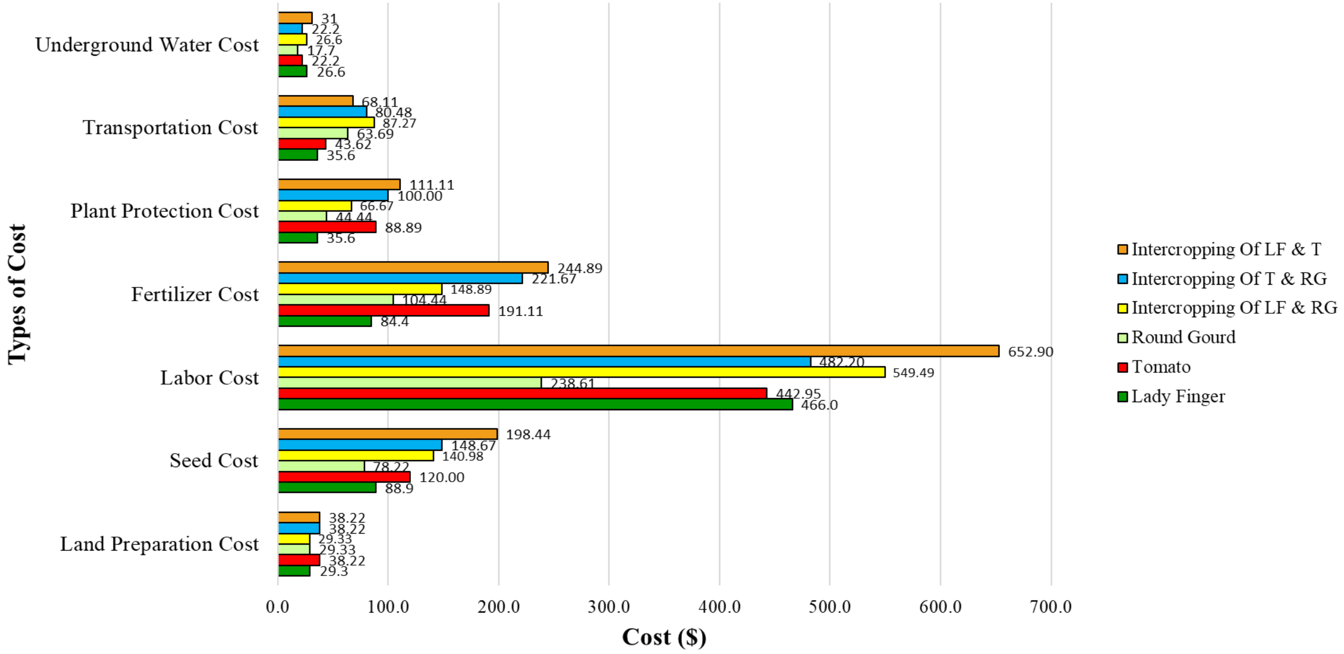


Figure 5.7: Types of cost for crop i per acre

The labor cost contributes 53% to the overall cost of production (see Figure 5.3). The highest per acre cost is also labor cost. Labor is required by each crop at every step thorough out the time period. Fertilizer cost is the second highest cost per acre, while seed cost is the third per acre highest cost for each crop. Figure 5.7 is observed that intercropping of ladyfinger and tomato has the highest cost of each cost type except the transportation cost. The highest transportation cost is incurred on the intercropping of lady finger and round gourd followed by the intercropping of tomato and round gourd. Land preparation cost is the same for tomato, the intercropping of ladyfinger with tomato, and intercropping of tomato with round gourd.

5.7 Comparison of farming approaches:

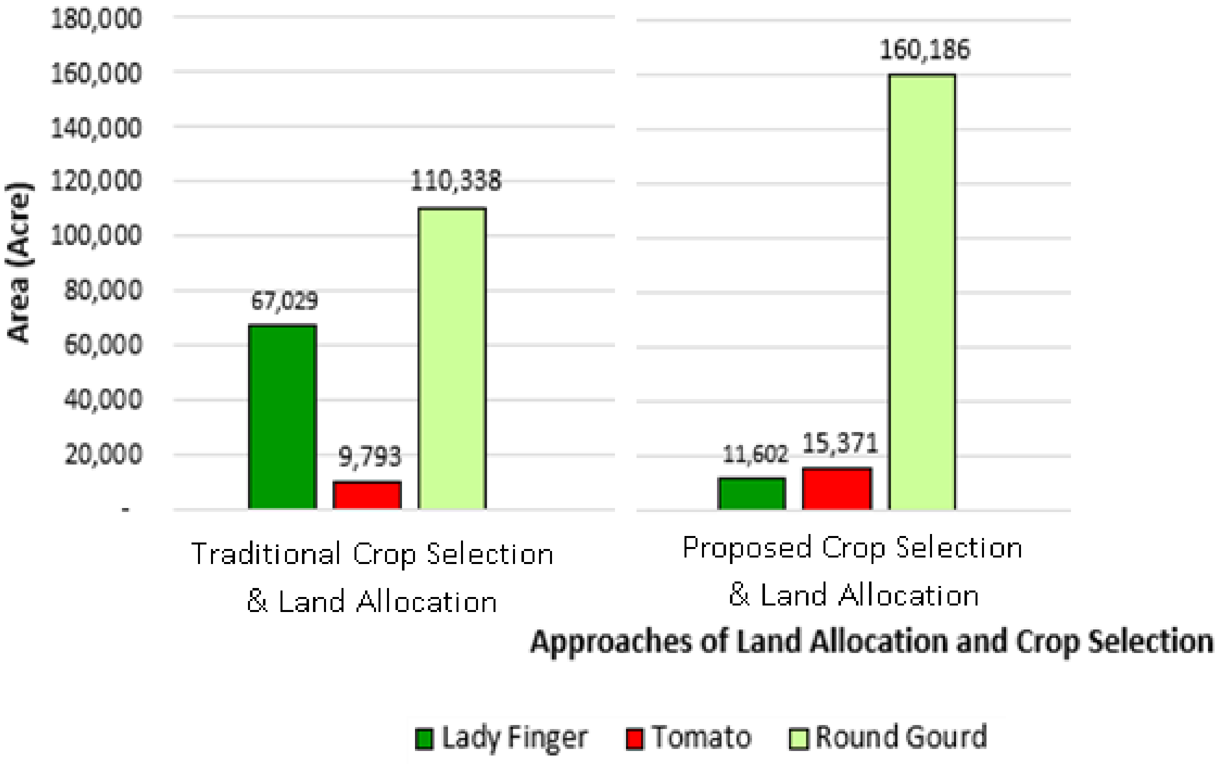


Figure 5.8: Comparison of traditional and proposed crop selection and land allocation (Area-wise)

The purpose of the mathematical model was to achieve optimum results. The method of crop selection and land allocation that is practical in the selected zone is considered a traditional farming approach, and the selection of crops and allocation of land at the optimum point of the mathematical model is considered a proposed approach. Now looking into Figure 5.8, it shows the comparison of the traditional approach and the proposed approach. For testing, only three crops are selected to show the efficiency of the model. Only lady finger, tomato, and round gourd are selected. The allocation of land for the traditional approach is based on the ratio of land allocated to these crops. From Figure 5.8, there is a difference between the allocation of both approaches and the inefficiencies.

The percentage comparison of traditional framing practice and the proposed without-intercropping approach is shown in Figure 5.9. If the approach of farming is shifting from the traditional approach to the proposed approach, the percentage changes in each objective value are shown. In the traditional farming approach, only profit is the priority, while in the proposed approach, profit is the highest priority with other objectives as well. Shifting to the proposed approach gives a 21.1% increase in the total revenue of the same amount of land in the same zone. The second objective is affected negatively, and it decreases the number of working opportunities by 18.06%. And the amount of yield will increase by 14.71%.

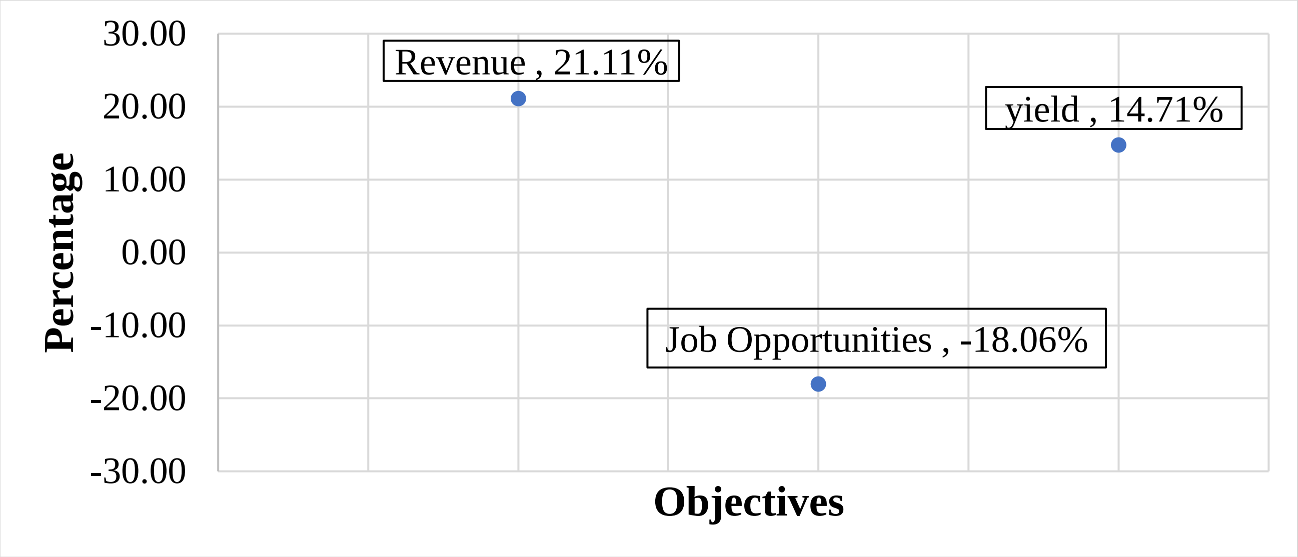


Figure 5.9: Percent change in each objective of proposed approach (Comparison of traditional to proposed approach)

This study focuses on intercropping with sole crops. The above figures show the comparison of two approaches without intercropping. Now consider intercropping as a crop and comparing to the two approaches. The first approach is the traditional farming approach, the second is proposed without intercropping approach, and the third and last one is proposed with intercropping approach. The same amount of land allocated to six crops, including intercropping, shows different results in Figure 5.10 compared to Figure 5.8. In the traditional approach, 67,029 acres of land are allocated to ladyfinger, 9,793 acres are allocated to tomato, and 110,338 acres of land are allocated to round gourd. While in the proposed approach, 11,602 acres of land is allocated to lady finger, 15,371 acres of land is allocated to tomato, and the amount of land that is allocated to round gourd is 160,186 acres.

The results of the proposed approach with intercropping are shown in Figure 5.10. As multi objectives have been considered, 11,602 acres of land is allocated to ladyfinger, which is the same as the proposed approach without intercropping. There is no change in the land allocation to tomato from the proposed approach without intercropping to the proposed approach with intercropping. The change occurs in round gourd allocation. From previous results, round gourd gives high yield and profit, but still, its allocation to land decrease to 5,475 acres in the proposed with the intercropping approach. Because here, the intercropping has been considered, and intercropping of lady finger and round gourd gives better results from the perspective of each objective and thus allocated to 154,712 acres of land.

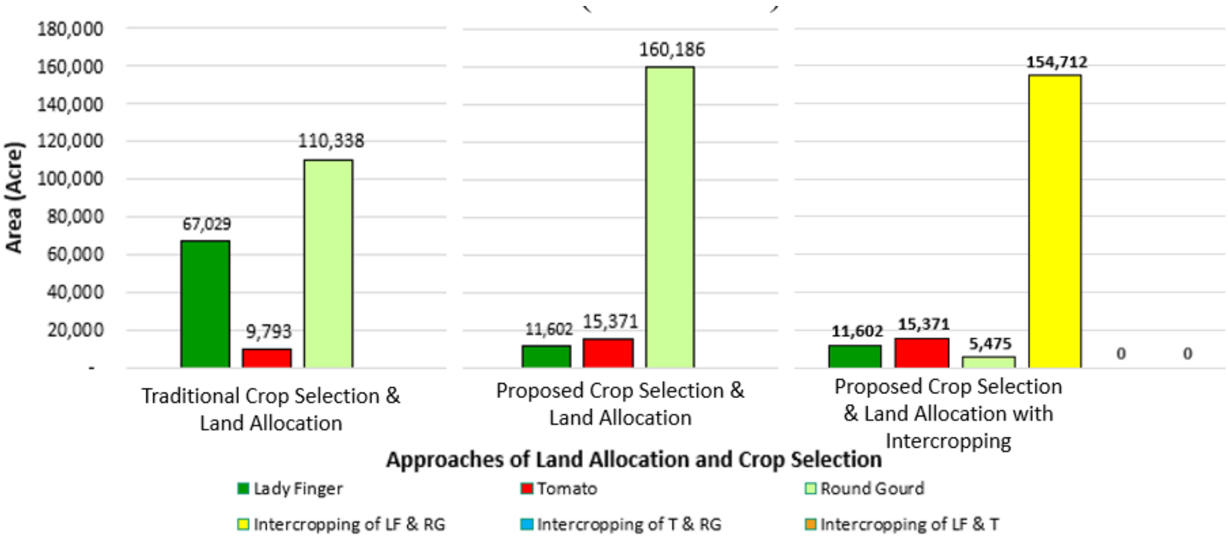


Figure 5.10: Comparison of traditional, proposed and proposed with intercropping crop selection and land allocation (Area-wise)

Figure 5.11 shows the comparison of the traditional farming approach and the proposed with intercropping approach in percentage. Proposed with intercropping approach consider multi objectives and intercropping practices. The amount of land for both approaches is the same. This figure shows the results that intercropping is either better or not in terms of desired objectives.

Hence it is observed that transforming from a traditional farming approach to a proposed with intercropping gives a 48.2% increase in revenue, 59.18% of working opportunities will increase, and the total amount of food will increase by 50.85%. These measures are better than the proposed without intercropping approach as well. In the proposed without intercropping, the generated revenue and yield were less than those proposed with intercropping and gave better results compared to the traditional approach, while the social factor decreased by 18%.

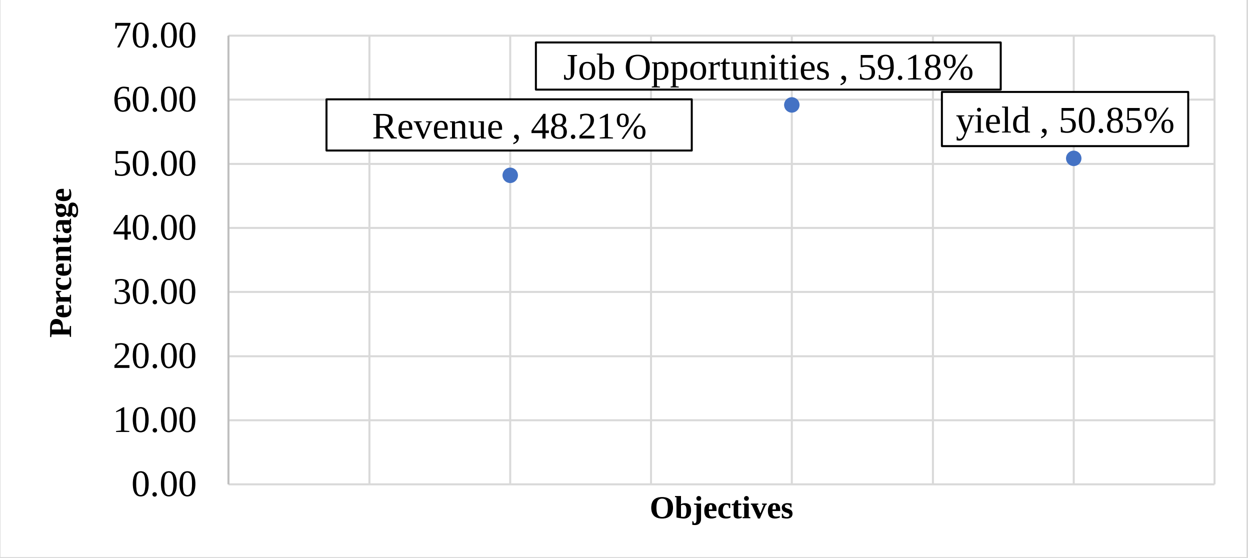


Figure 5.11: Percent change in each objective of proposed approach (Comparison of traditional approach of farming to proposed with intercropping approach)

5.8 Sensitivity analysis

A Sensitivity Analysis is performed for a few key parameters of the mathematical model that are used to develop the multi-objective model for agriculture farming land. The values of key paraments are changed by specific percentages in order to record the change in optimal results of all objective functions, including maximization of profit, maximization of working days, and yield maximization under uncertain yield. For the sensitivity analysis, the change in percentage is fixed to show the change in optimal values of objective functions for each parameter. The considered percentage change is +50%, -50%, +25%, -25%. The sensitivity analysis is performed for four key parameters at land type 1 that is irrigated by canal water. Those four parameters include the demand of crop *i*, the yield of each crop, the available land of each land type, and the cost types that have a high percentage share of the overall cost of production. The result of the sensitivity analysis of key parameters is shown in Table 5.6.

Table 5.6: Sensitivity analysis of few parameters

Parameter	Crops	% Change	Profit ($) % change	Jobs (Days) % change	Yield (kg) % change
(Demand)	Lady Finger	50%	-3.763	-0.491	-2.018
		25%	-1.881	-0.246	-1.009
		-25%	1.881	0.246	1.009
		-50%	3.763	0.491	2.018
	Tomato	50%	-4.457	-0.831	-2.256
		25%	-2.228	-0.415	-1.128
		-25%	2.228	0.415	1.128
		-50%	4.457	0.831	2.256
	Round Gourd	50%	-0.019	-0.864	-0.433
		25%	-0.009	-0.432	-0.217
		-25%	0.009	0.432	0.217
		-50%	0.019	0.864	0.433
Yield	Lady Finger	50%	24.08	0.328	16.26
		25%	11.67	0.197	8.29
		-25%	-5.18	-47.912	-26.03
		-50%	-12.79	-46.133	-29.21
	Tomato	50%	7.46	-10.360	13.41
		25%	3.44	0.332	1.81
		-25%	-5.74	-0.554	-3.01
		-50%	-17.21	-1.662	-9.03
	Round Gourd	50%	70.22	-48.812	9.88
		25%	34.37	-48.812	-7.32
		-25%	-37.75	-0.195	-17.26
		-50%	-70.78	-1.731	-33.63

Table 5.6: Sensitivity analysis of few parameters (Continued…)

Land	Canal Water	50%	54.40	74.35	50.94
		25%	27.19	25.72	23.13
		-25%	-27.17	-11.09	-24.82
		-50%	-54.36	-39.58	-50.07
	Underground water	50%	3.02	20.58	3.27
		25%	1.52	18.99	1.85
		-25%	-1.50	-1.35	-0.98
		-50%	-2.70	-2.42	-2.55
	Rainwater	50%	0.88	19.24	1.80
		25%	0.43	17.16	0.69
		-25%	-0.41	16.46	-0.25
		-50%	-0.84	15.54	-0.94
Costs	Fertilizer cost	50%	-7.05	-48.81	-24.49
		25%	-3.75	16.24	-1.86
		-25%	3.75	0.00	0.00
		-50%	7.50	0.00	0.00
	Labor Cost	50%	-15.36	-48.81	-24.49
		25%	-8.06	-48.81	-24.49
		-25%	13.62	0.00	0.00
		-50%	27.15	0.00	0.00
	Seed Cost	50%	-5.58	-48.81	-24.49
		25%	-3.46	-1.32	-0.66
		-25%	3.46	0.00	0.00
		-50%	6.93	0.00	0.00

5.8.1 Sensitivity analysis of demand:

Figure 5.12 it is shown the effect of changing demand for ladyfinger by a specific percentage on each objective function. Decreasing the demand affects the objective functions the same as increasing the demand but in the opposite direction. From the figure, it is observed that the change in objective functions value is linear with the percent amount. The demand change of ladyfinger affects each objective; the economic objective is affected more percentage-wise comparatively to other objectives. While the social objective is affected less comparing to the remaining two.

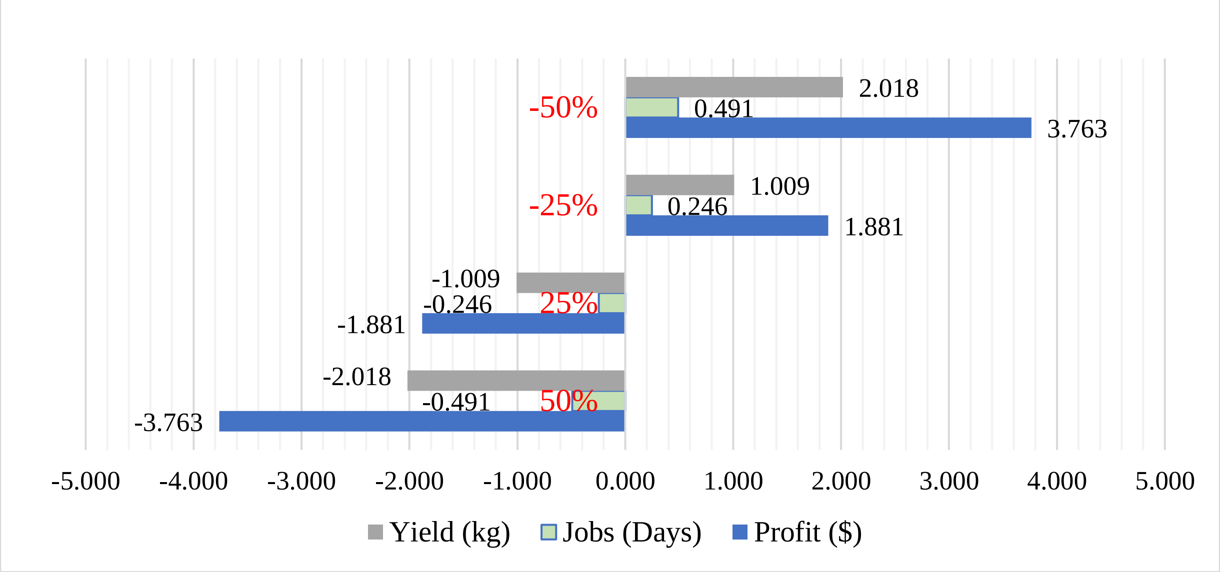


Figure 5.12: Effect of changing demand of lady finger on objectives for sensitivity analysis

The effect of changing demand for tomato on objectives as shown in Figure 5.13. Changing the demand by the same percentage as for lady finger (figure 19), comparing both Figure 5.12 and Figure 5.13, it is concluded that the effect on profit is high for tomato than ladyfinger. Considering the second objective, ladyfinger has less effect in comparison to tomato, and changing demand for tomato also has more effect on the overall yield. The effect of changing demand has a linear trend.

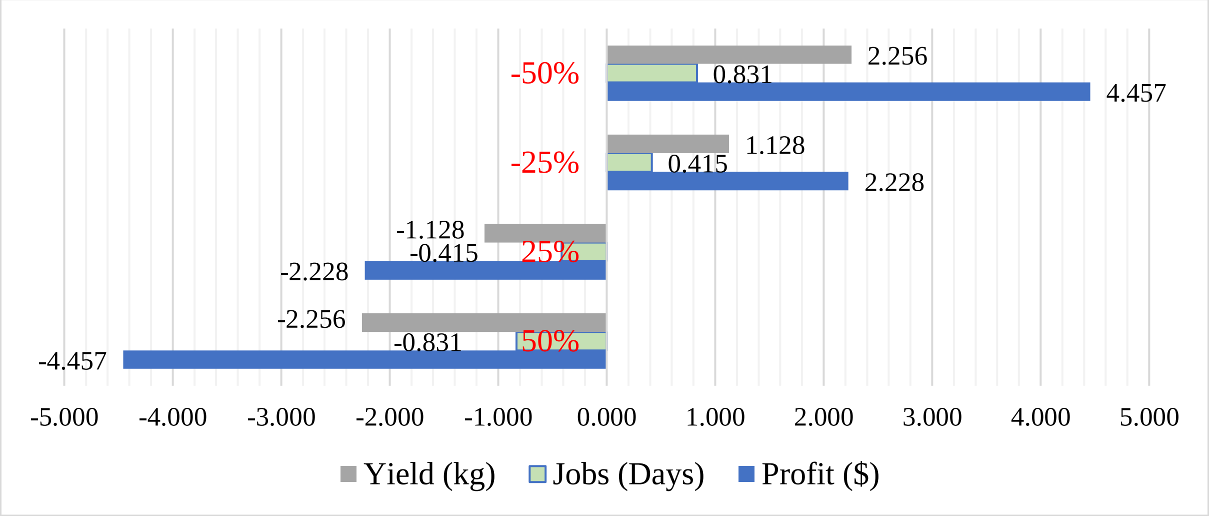


Figure 5.13: Effect of changing demand of tomato on objectives for sensitivity analysis

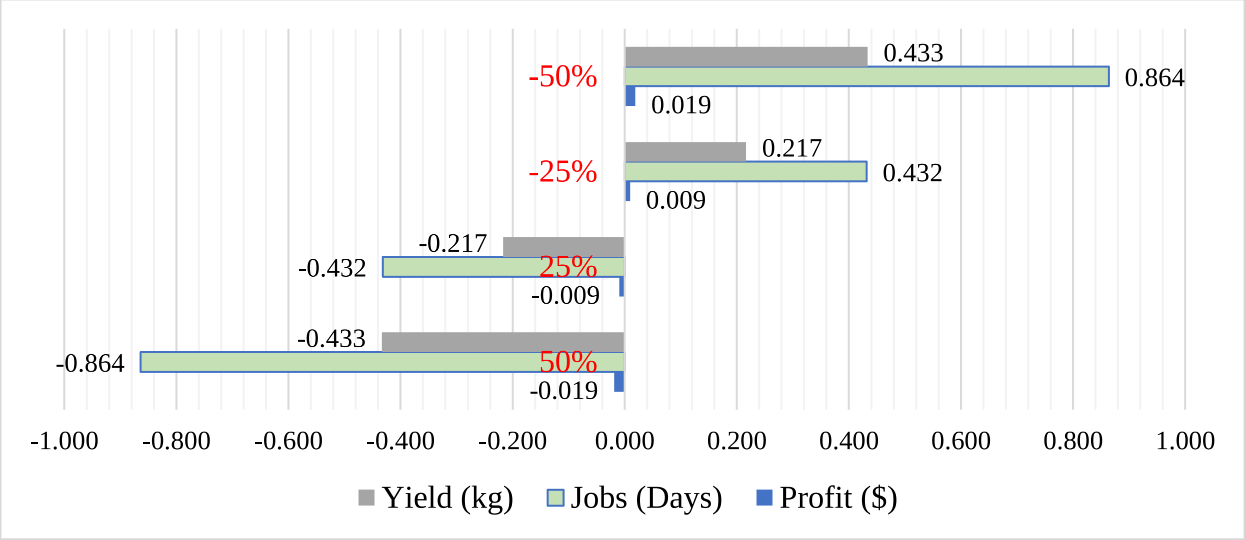


Figure 5.14: Effect of changing demand of round gourd on objectives for sensitivity analysis

Sensitivity analysis for the demand parameter is shown in Figure 5.12, Figure 5.13, and Figure 5.14 for crops including lady finger, tomato, and round gourd, respectively. Comparing all three figures, it is clear that with demand changing, the effect shows linear behavior for each objective. It has been observed that tomato has a high effect on objectives if a change occurs in demand, while the effect of changing demand of round gourd shown in figure 5.14 has the least effect of each objective in comparison with lady finger and tomato. The production rate of round gourd is higher than both ladyfinger and tomato. Changing its demand makes less change in the allocation of land. All these values of objectives are dependent on the amount of land allocation. That is the reason why round gourd has less effect, as the production rate per acre is high.

5.8.2 Sensitivity analysis of yield:

The production rate of crops depends on several factors. These factors may be natural conditions, input resources, types of seed, soil health, etc. For the realistic purpose, the yield is taken uncertain and converted to the deterministic value. Variation in the production rate of crops is a serious issue and directly affects the values of desired objective functions. The economic perspective is directly linked with production. If the production rate is increasing, ultimately, the profit will increase, and as the production rate is going to decrease, the overall profit will go to decrease that effect farmer financing and the GDP of country.

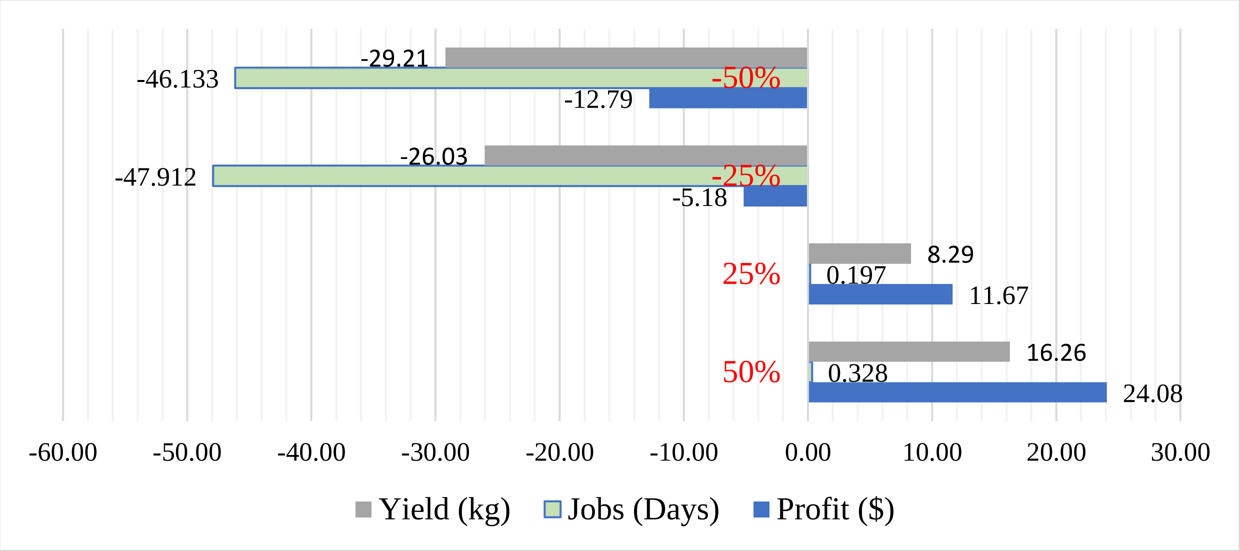


Figure 5.15: Effect of changing average production rate of lady finger on objectives

However, the social factor almost remains unaffected more by increasing or decreasing the production rate. So, the amount of working opportunities remains almost the same. In contrast, national food security is highly affected by the variation in the rate of production of crops. Figure 5.15 shows the effect of changing the average production rate of ladyfinger on each objective function value. Here are some interesting results in this figure. Considering the working days (jobs), as the production rate is increasing, there is negligible effect on the overall job opportunities, while if the production rate is decreasing, then the number of working days decreases with a high percentage. Another critical point of the result is changing the production rate by 25 percent shows a high impact, while the change of 50 percent shows less effect.

The effect of changing the average production rate of ladyfinger shows that it has a high effect on social objectives, as shown in Figure 5.15. From the figure, it is observed that if the production rate is increased by 25%, the change in social objective is 0.197%, while increasing the production by 50% gives a 0.328% change in social objective value. On the other hand, if the yield of ladyfinger is decreased by 25%, the change in the social objective is a 47.9% reduction. While decreasing the yield by 50% gives a reduction of 46.1%. Here a non-linear change is observed. As the change in yield rate is linear and at a specific amount of percentage, the results and its impact on social objectives are not linear. The reason behind this is the model is solving a set of constraints, and the allocation is changing considering the limit of parameter values.

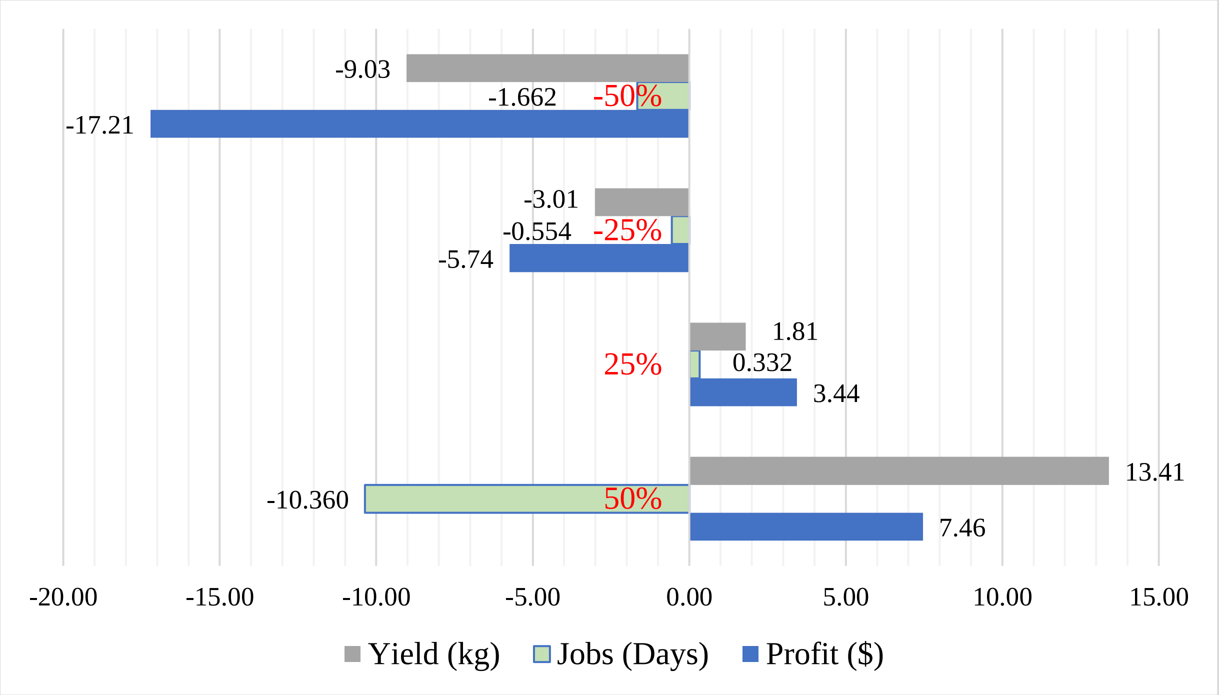


Figure 5.16: Effect of changing average production rate of tomato on objectives

Figure 5.16 shows the effect of variation in the production rate of tomato on each objective. These effects may change by changing some parameters, like the selling price of crops. Here it is observed that the change in profit is not linear behavior as changing the production rate of tomato by 50 percent increase results in a 17.21 percent decrease in profit while increasing the production rate with the same amount of 50 percent shows a 7.46 percent increase. Considering the social aspect, the amount of working opportunities (Jobs) is decreasing by decreasing the production rate of tomato. In contrast, the value decreased when the average production rate was increased by 50 percent. This depends on the allocation of land to different crops and a set of constraints. The total yield is increasing with increasing average production rate of tomato while decreasing with decreasing the rate of tomato production.

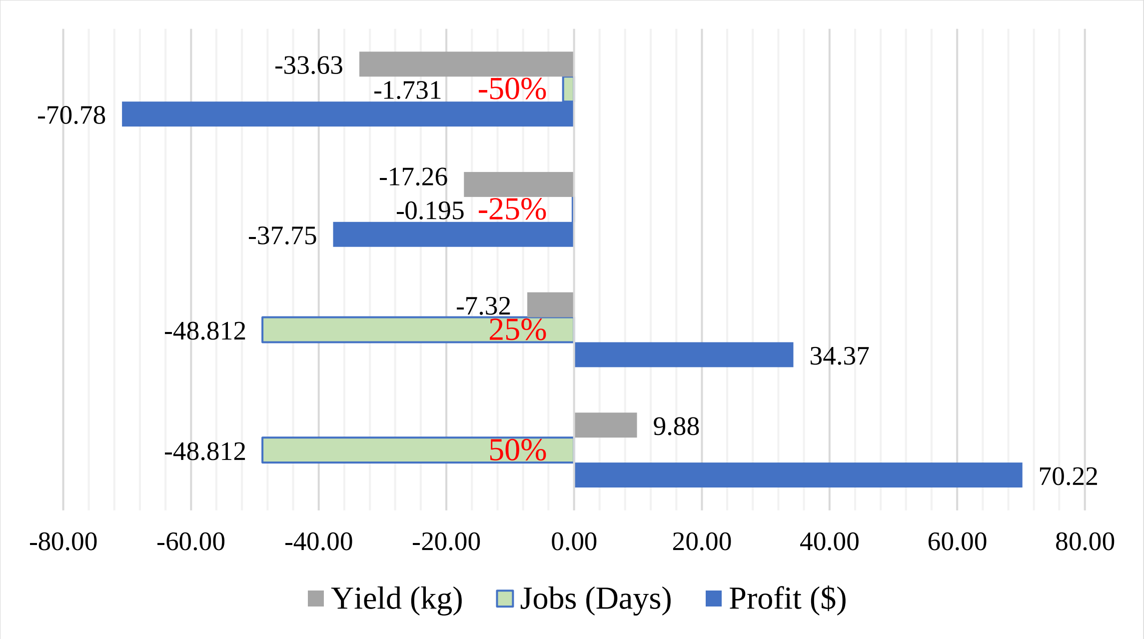


Figure 5.17: Effect of changing average production rate of round gourd on objectives

The effect of varying the production rate of round gourd on each objective value is shown in Figure 5.17. The economic aspect is affected more by both increasing and decreasing of the production rate of round gourd. Overall yield is affecting less compared to economic objective. But the distinct nature of the social aspect shows that if the average production of round gourd increases, it decreases the total working days by a negligible amount, while increasing the production rate of round gourd still decreases the value of the social objective. The reason behind this fact is round gourd need a low amount of working days. If the production rate is increasing thus, it needs less amount of land and, consequently, less amount of workers need.

Comparing the effect of changing the production rate of each crop per acre at a specific amount of percentage, including +50%, +25%, -50%, and -25%, shows that round gourd is more important from the perspective of profit. Round gourd shows a high effect on economic function by changing the production rate in comparison to other crops. The total amount of yield is affected more by varying the average production rate ladyfinger compared to other crops. And from a social aspect round gourd is more important and shows high deviation by changing the production rate with a specific amount of percentage. Tomato has an average effect on each objective value and has more effect on the economic objective.

5.8.3 *Sensitivity analysis of major cost types:*

The total cost incurred on the production of crops is categorized into several types of cost. Each type of cost is contributed by a specific percentage to the amount of total cost. Cost is an important parameter that has a direct impact on the desired objectives, including economic, social, and food security. Figure 5.18 shows the effect of varying costs of ladyfinger with a specific percentage on each objective. From the figure, it is observed that decreasing the cost of fertilizer has no effect on the social objective and yield objective. It has increased the profit by 7.50 percent if increased by 50 percent. Decreasing 25 percent of fertilizer cost shows a 3.75 percent increase in total profit. In case the cost of fertilizer increases, the social aspect will be affected more in comparison with yield and economic objectives.

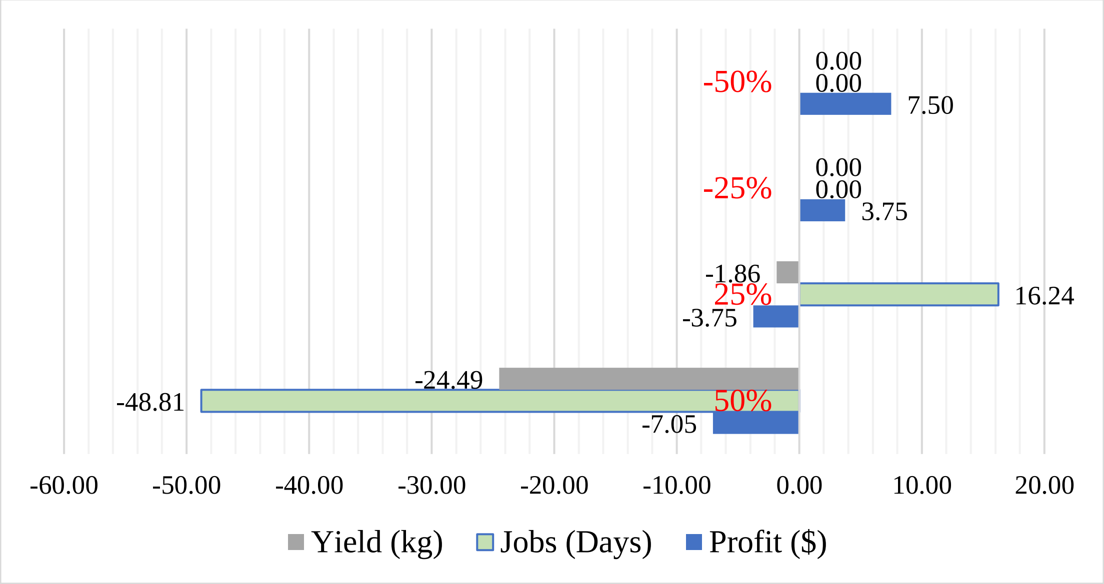


Figure 5.18: Effect of changing fertilizer cost on each objective value

Figure 5.19 shows the changes in labor cost by a specific percentage and its effect on each objective function value. Decreasing labor cost show zero effect on both social objective and overall yield. The only effect of decreasing labor costs is on economic objectives, and it is quite clear that reducing costs leads to an increase in profit. On the other hand, increasing the labor cost by the same amount of percentage as decreasing shows the same effect on overall yield. The effect of decreasing labor cost is constant for overall yield and social objective, whatever the decreasing value of percentage for labor cost. The only effect of that is changing with changing the percentage of decreasing labor cost is on the economic objective. And the absolute amount of profit gained by decreasing labor costs by 50 percent is not the same as increasing the labor cost by 50 percent.

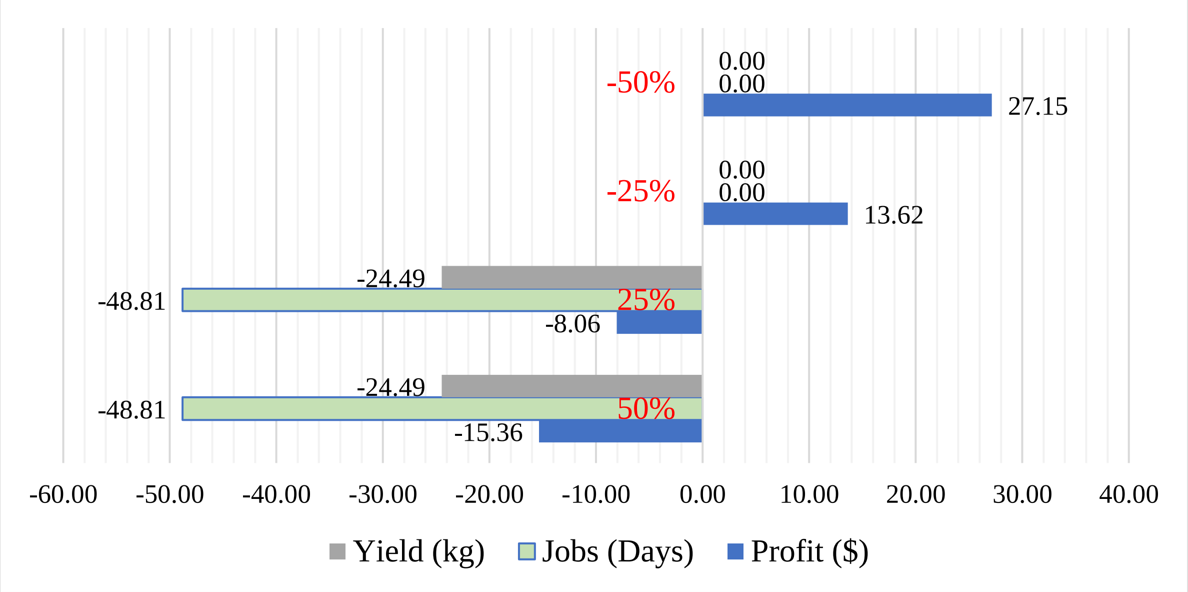


Figure 5.19: Effect of changing labor cost on the value of each objective

Major costs include labor costs, fertilizer costs, and seed costs. Figure 5.20 shows the sensitivity analysis of seed cost. It is observed from Figure 23 that decreasing seed cost has no impact on the number of working opportunities (days) and overall yield by changing the value by a specific amount of percentage. It shows zero effect for increasing the price on two objectives but has an impact on the economic objective. Increasing the value of seed cost by 50 percent shows a 5.58 percent decrease in overall profit while showing a 3.46 percent decrease in total profit if the seed cost increase by 25 percent. On the other hand, decreasing the seed cost by 50 percent shows a 6.93 percent increase in overall profit, and changing the seed cost to a 25 percent decrease shows a 3.46 percent increase in the overall profit. The effect of increasing seed cost by 25 percent shows a 0.66 percent decrease in overall production and decreasing working days by 1.32 percent. A percentage change of 50% shows the effect of a 24.49 percent decrease in overall production and a 48.81 percent change in the working days.

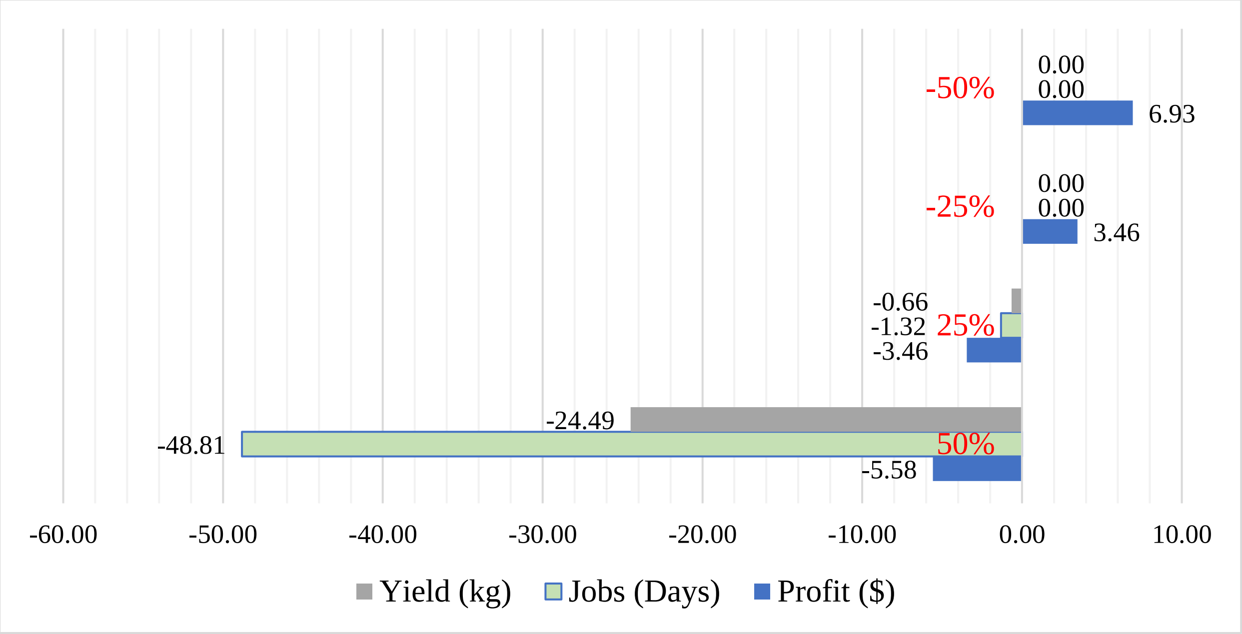


Figure 5.20: Effect of changing seed cost on the value of each objective

The above figures depict the effect of changing seed cost with a certain percentage of each crop on each objective value. Labor cost has a major contribution to the overall cost in comparison to other types of cost and hence shows a high impact on the objectives. If the cost varies by some amount of percentage, either increasing or decreasing. An interesting result has been observed from the sensitivity analysis of major costs. It shows that if the cost is decreasing from the original value by a specific amount of percentage, resulting no change in the value of two objective values. Those two objectives are social and yield. In contrast, it affects the economic objective and depends on the amount of percent change. On the other hand, considering the social factor, the above all three figures for costs shows that the jobs are decreasing by a fixed percentage of 48.81 percent if increasing any cost type by 50 percent.

In this research, only three main types of costs are selected for sensitivity analysis. The selection is based on the contribution of these cost types to the overall cost of production. Sensitivity analyses give insight into key parameter variation and its impact on the objectives. In this study, the sensitivity of the parameters is measured by the percent change. The result of changing parameter values is recorded in percentage, and comparisons have been made. From each type of parameter, the most important sub-type is selected that shows a high impact on the result if a change has been made in its value.

Sensitivity analysis can be studied from different perspectives. Instead of changing parameter values by a specific percentage, they can be changed by the same amount and should be studied. For example, there are three types of costs that are involved in an operation. If the cost is increased by $10 each, now the situation is different, and it will give a unique result because each type of cost is increased by $10. And percentage change is not showing a clear and correct impact on the overall solution. In such case, that type of parameter will be a key parameter which requires more in amount..

Sensitivity analysis reveals the relative importance of the assumptions and input parameters used in the model. It differs from uncertainty analysis, which deals with the issue of "How uncertain is the prediction?" Both a sensitivity analysis and an uncertainty analysis must map what a model behaves when certain input assumptions and parameters are allowed to fluctuate within the range of possible values. Despite this, many uncertainty and sensitivity assessments continue to go down one-dimensional corridors to investigate the input space, mostly ignoring the space of the input variables (Saltelli et al. 2019).

Sensitivity analysis has an obvious role in the verification, validation, and calibration procedures. Understanding the sensitivity of the accompanying evaluations and credibility measurements to the specific elements in the code parameterizations is essential in all instances of the verification, validation, and calibration formalism proposed (Trucano et al. 2006). The research-based response to model uncertainty is guided by parameter sensitivity. Sensitivity analysis directs parsimony, which is the decrease of the size of the parameter vector and is still a crucial model selection criterion. To put it another way, sensitivity analysis is necessary to determine how complex a model is while yet remaining plausible.

In its broadest definition, sensitivity analysis is the study of how a "system's" "outputs" relate to and are impacted by its "inputs." Why sensitivity analysis? It briefly tackles a number of the fundamental and overarching goals of systems analysis and modeling, including: (a) Investigating causal relationships and how various processes, hypotheses, factors, and scales impact a system via combinations and interactions (Gupta and Razavi 2018), (b) dimension reduction to find redundant or insignificant variables in a system that may be corrected or eliminated in later investigations (Tarantola et al. 2007), and (d) Using decision support, one may measure how sensitive an expected result is to various restrictions, assumptions, and/or uncertainties (Tarantola et al. 2002).

Despite all these advances, a number of obstacles have prevented the advantages and true promise of SA throughout the sciences from being realized (Razavi et al. 2021). The fact that sensitivity analysis is still a paradigm characterized mostly by procedure rather than goal is among the most serious challenges. particular techniques have been created, each based on a particular philosophy of sensitivity analysis (Razavi and Gupta 2015). But frequently, the goal has been established based on the operation and capabilities of a certain technique as well as the disciplinary research interests of its creators. The benefits of sensitivity analysis can be hidden from academics and practitioners by narrow viewpoints, a lack of cross-disciplinary collaboration, and neglecting uncertainties in models. As a result, many modeling branches underuse SA, which undermines model-based policymaking (Saltelli et al. 2019).

6. Conclusion

In this research, a multi-objective multi-product single-period decision support tool is presented to assess the productivity, profitability, and social impact of the agriculture sector, specifically the farming of crops. Few crops are selected for this study, including lady finger, tomato, and round gourd. In literature, such type of work is performed with linear programming and non-linear approaches. The additional contribution of this research is to study intercropping with solo crops using mathematical programming. The intercropping of only two types of crops at a time on the same field is considered as a separate crop that includes the intercropping of ladyfinger with tomato, intercropping of ladyfinger with round gourd, and the intercropping of tomato with round gourd.

The zone that is considered for this study is Peshawar, and all of the available agricultural land of Peshawar is considered. Total available land is categorized into three types on the basis of water availability. The first type of land is known as canal water land. This land type is irrigated through canal water and surface water. The second type of land is known as underground water land, and this land is irrigated through tube wells and wells. Rainwater is also considered for both of the above land types. Considering the rain forecasting, the amount of water is provided in computation. The third type of land is rainwater land that is only irrigated through rainwater.

The augmented Epsilon Constraint method is applied to solve the multi-objective mathematical model. MATLAB R2018a is used as a solving tool for the model. This method is easy to use and better suited for multi-objectives problems when there is a contradiction among the objectives. In this study, the three objectives are studied. The first one is economic, which maximizes the profit. The second objective is social, which creates job opportunities, and the third one is national food security, which maximizes the overall production of the available land in order to fulfill the basic food requirement of the population.

The overall cost of production is classified into seven types, including labor cost, land preparation cost, fertilizer cost, seed cost, irrigation cost, plant protection cost, and transportation cost. Packaging cost is not included in this study. The average production rate of each crop per acre is taken as uncertain. A distribution fitter tool has been used to find the best distribution for the past data in order to get the best estimated deterministic value of the parameter. Each crop has a unique pattern of production over time and thus may follow different distribution and has expected value accordingly.

The results that are obtained from the proposed multi-product multi-objective model validate and support the desired objectives set in this study. The results show that there are inefficiencies in the traditional method of farming and transforming from the traditional method of farming to the proposed method gives better results considering each objective except the social objective. That show negative result comparatively. As the high focus of this research was on optimum crop selection and land allocation, the comparison of solo crop output with the intercropping approach. Proposed with intercropping approach shows positive results in each objective function value.

Intercropping shows better results in term of profit maximization, creating more job opportunities per unit of land in comparison to solo crops and giving a high amount of production that minimize the risk of hunger. There are seven types of cost, where the major contribution is labor cost, fertilizer cost, and seed cost. Labor cost shows a contribution of more than half of the total production cost. The sensitivity analysis is performed for key parameters of solo crops only. The demand for tomato has a high impact on objectives comparatively, the yield of round gourd effect the objectives more in comparison to other crops, and labor cost has a major impact on each objective among all types of costs.

6.1 Practical Implications:

The effectiveness of the multi-objective model is to evaluate the potential and performance of available land and the utilization of limited resources. It facilitates the direct farmers; they can easily manage their resources to achieve high profit and will also consider food security and the social perspective of the study. Decision makers of food organizations can use this model to plan for inventory and prior planning of procurement if the requirement cannot be fulfilled by the available resources. The agriculture department and other direct and indirect firm of farming crops can get benefits from the model to utilize their resources effectively. The model is robust and can be utilized in any geological location. Many organizations that are related to businesses are investing in food and agriculture. This study is helpful in their decision-making with authentic and realistic estimation of output in their operating area.

6.2 Limitations and Future Implications:

This research is performed for specific crops section like vegetables. In a real scenario, there are other crops, including root crops, grain crops, medicinal plants, grasses, fruit plants, and major crops like wheat, corn, cotton, etc. Future research can study the mix of all other types of seasonal crops. The main input resources required for farming are considered available for this study. Research should be performed on the exact availability of input resources with water management and achieve maximum utilization. The intercropping of only two crops at a time is studied, and future studies may target all possible intercropping combinations with a multi-time period model.

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Appendix A:

Table A.1: Selling price of each crop (AIMS Pakistan)

S. No	Crop Type	Value PKR
1	Ladyfinger	59
2	Tomato	69
3	Round gourd	81
4	Intercropping of ladyfinger and round gourd	74
5	Intercropping of tomato and round gourd	76
6	Intercropping of lady finger and tomato	65

Table A.2: Land preparation cost of each crop per acre
(Kshash et al., 2022) (Ahmad et al., 2019) (Kushwaha et al., 2018)

S.No	Crop Type	Value PKR/Acre
1	Ladyfinger	6,600
2	Tomato	8.600
3	Round gourd	6,600
4	Intercropping of ladyfinger and round gourd	6,600
5	Intercropping of tomato and round gourd	8,600
6	Intercropping of lady finger and tomato	8,600

Table A.3: Seed cost of crop i at land type j in location k
(Kshash et al., n.d. 2022), (Ahmad et al., 2019)

S.No	Crop Type	Value PKR/Acre
1	Ladyfinger	20,000
2	Tomato	27,000
3	Round gourd	17,600
4	Intercropping of ladyfinger and round gourd	31,720
5	Intercropping of tomato and round gourd	33,450
6	Intercropping of lady finger and tomato	40,650

Table A.4: Required working hour
(Interviews, CRS, Peshawar)

S.No	Crop Type	Value hr/Acre
1	Ladyfinger	748
2	Tomato	711
3	Round gourd	383
4	Intercropping of ladyfinger and round gourd	882
5	Intercropping of tomato and round gourd	774
6	Intercropping of lady finger and tomato	1048

Table A.5: Worker wage rate

S.No	Description	Value
1	Wage rate	700 PKR/day
2	Max. working capacity of worker/day	5 hr

Table A.6: Fertilizer cost for crop i per acre
(Kshash et al., n.d. 2022), (Mahamuda Parvin & Mizanur Rahman Sarker, 2021),

S.No	Crop Type	Value PKR/Acre
1	Ladyfinger	19,000
2	Tomato	43,000
3	Round gourd	23,500
4	Intercropping of ladyfinger and round gourd	33,500
5	Intercropping of tomato and round gourd	49,875
6	Intercropping of lady finger and tomato	55,100

Table A.7: Plant protection cost for crop i per acre
(Kshash et al., n.d. 2022), (Kushwaha et al., 2018), (Ahmad et al., 2019)

S.No	**Crop Type**	**Value PKR**
1	Ladyfinger	8,000
2	Tomato	20,000
3	Round gourd	10,000
4	Intercropping of ladyfinger and round gourd	15,000
5	Intercropping of tomato and round gourd	22,500
6	Intercropping of lady finger and tomato	25,000

Table A.8: Irrigation cost (underground water) for crop i per acre
(Kushwaha et al., 2018), (Kshash et al., n.d. 2022)

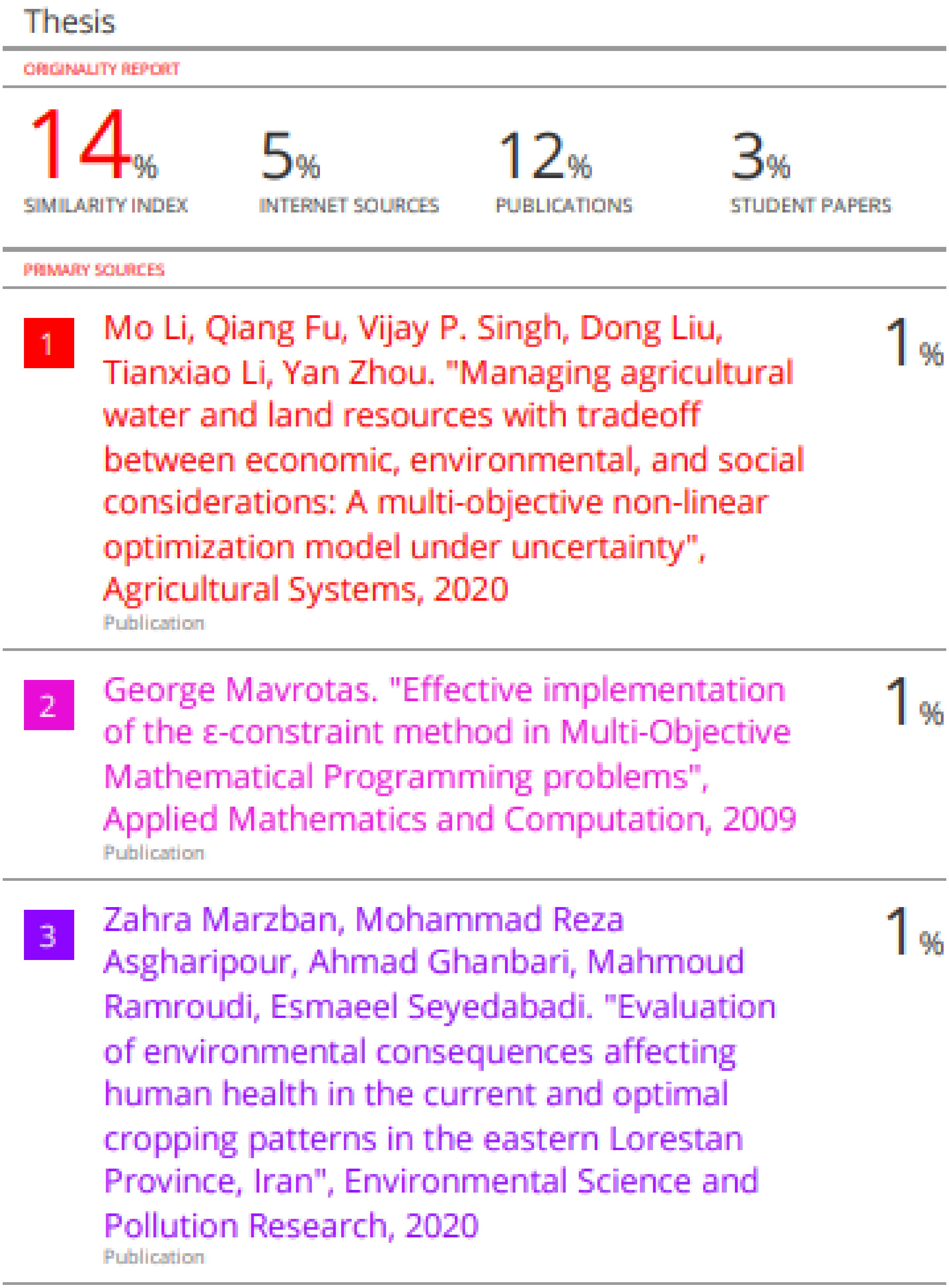
S.No	**Crop Type**	**Value (PKR/Acre)**
1	Ladyfinger	6,000
2	Tomato	5,000
3	Round gourd	4,000
4	Intercropping of ladyfinger and round gourd	6,000
5	Intercropping of tomato and round gourd	5,000
6	Intercropping of lady finger and tomato	7,000

Table A.9: Food demand per capita per year for crop i
(Amjad et al., 2020), (Shahnaz A. Arifullah*, 2008)

S.No	Crop Type	Value (kg/capita/yr)
1	Ladyfinger	20
2	Tomato	25
3	Round gourd	13

Table A.10: Average production rate of crop i at land type j in location k
(Mahmood Alam et al., 2019), (Khokhar, 2014), (Hassan et al., 2021),(Khan & Ali, 2013), (Mukhtar et al., 2017), (Das et al., 2021)

S.No	**Crop Type**	**(kg/Acre) (Canal water)**	**(kg/Acre) (Underwater)**	**(kg/Acre) (Rainwater)**
1	Ladyfinger	2,829	2,829	1698
2	Tomato	3,470	3,470	-
3	Round gourd	5,066	5,066	-
4	Intercropping of ladyfinger and round gourd	6,935	6,935	-
5	Intercropping of tomato and round gourd	6,402	6,402	-
6	Intercropping of lady finger and tomato	5,418	5,418	-



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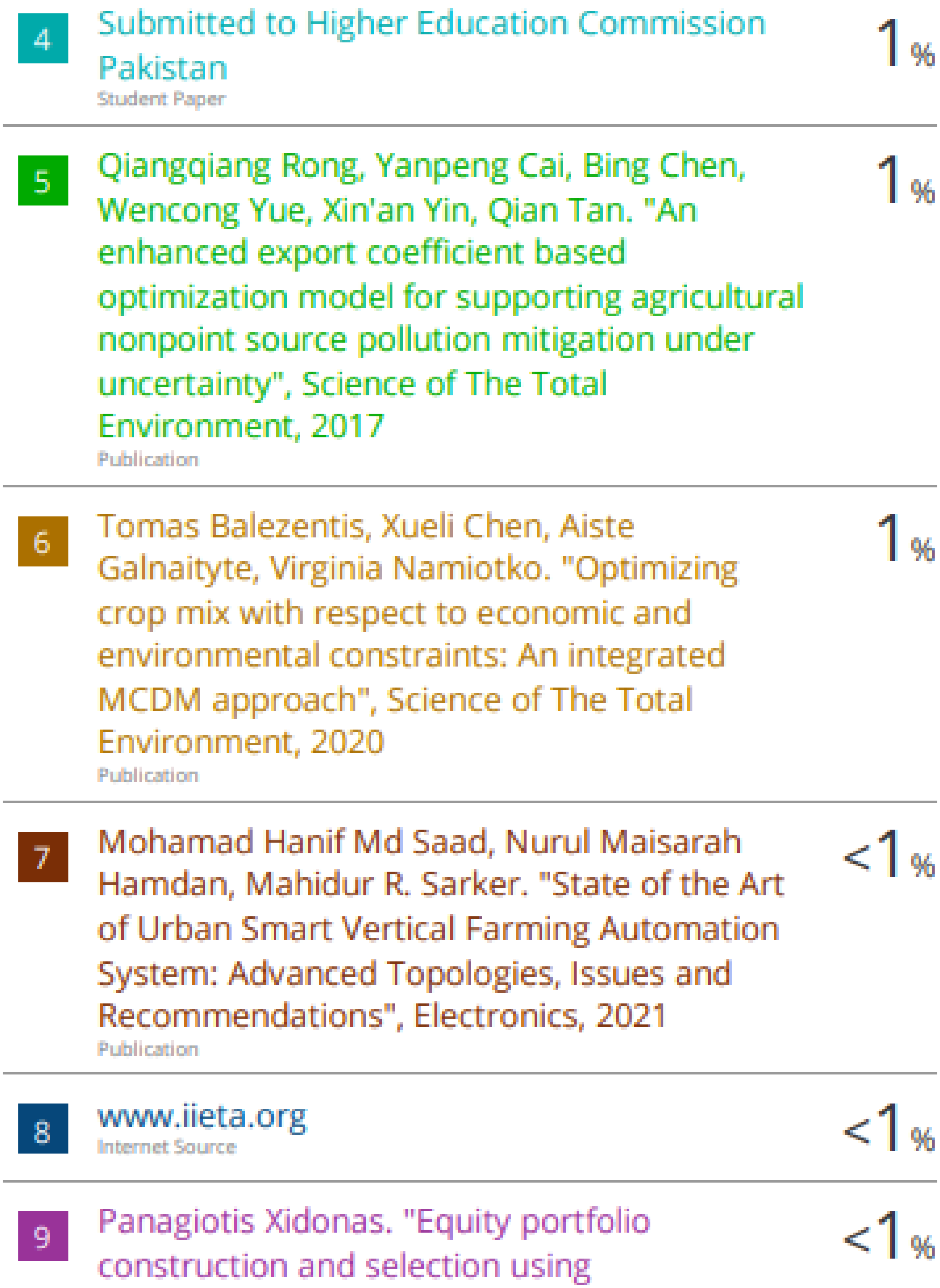

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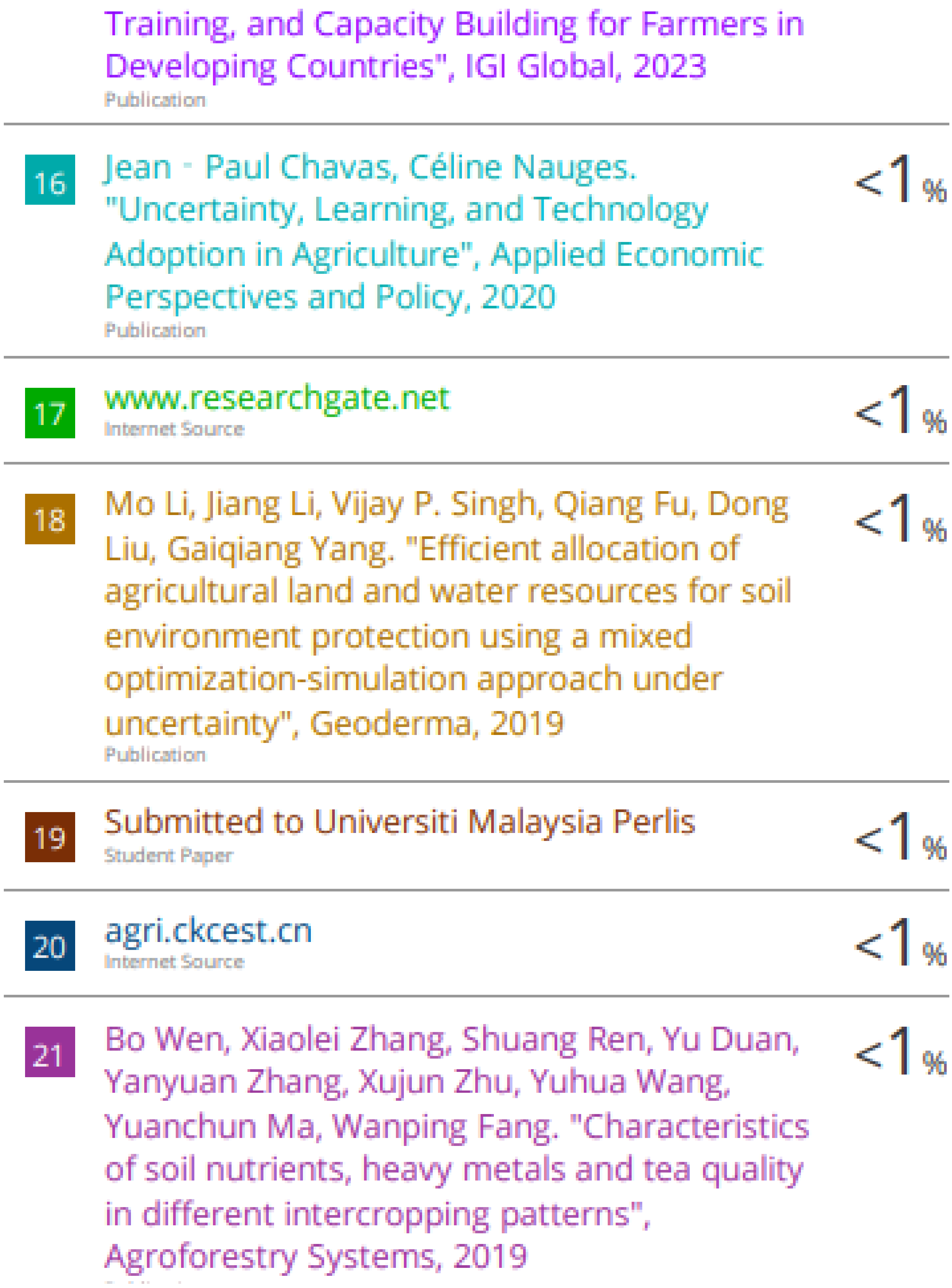

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