DIFFERENTIAL EVOLUTION ALGORITHM FOR OPTIMAL STRATEGIC DECISION MAKING IN CROP FARMING SYSTEM

By

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DECLARATION

I, Adekanmbi Oluwole Abayomi declare that this dissertation is a representation of my own work both in conception and execution. This work has not been submitted in any form for another degree at any university or institution of higher learning. All information cited from published or unpublished works have been acknowledged.

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DEDICATION

This dissertation is dedicated to my family for their support, encouragement and motivation throughout the period of this study.

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I would like to express my sincere appreciation to the Almighty God, for His never-ending love, awesomeness and amazing love and grace without which this would have been a futile exercise. I will forever love him.

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ACRONYMS

η_c	Distribution index for real variable crossover operation in NSGA-II
η_m	Distribution index for real variable polynomial mutation in NSGA-II
CD	Crowding distance
CR	Crossover control parameter of DE
D	Number of decision variables
F	Mutation control parameter of DE
G	Generation number
GD	Generational distance
$G_{\max}$	Maximum number of generations
IGD	Inverted generational distance
K	Number of constraints
M	Number of objectives
NP	Population size
ρ_c	Crossover probability of real variable in NSGA-II
ρ_m	Mutation probability of real variable in NSGA-II
S	Spacing
ACO	Ant Colony Optimization
DE	Differential Evolution
DEMO	Differential Evolution for Multi-objective Optimization
DE/rand/1/bin	DE strategy based on mutation of a random individual of the

	Population
EA	Evolutionary algorithm
EMO	Evolutionary Multi-objective Optimization
εMOEA	ε-dominance Multi-Objective Evolutionary Algorithm
ES	Evolutionary Strategy
FAO	Food and Agriculture Organization
GA	Genetic Algorithm
GDE	Generalized Differential Evolution
GDE1	First version of Generalized Differential Evolution
GDE2	Second version of Generalized Differential Evolution
GDE3	Third version of Generalized Differential Evolution
GDP	Gross Domestic Product
MOEA	Multi-objective evolutionary algorithm
MOEA/D	Multi-objective evolutionary algorithm based on decomposition
MOOP	Multi-Objective Optimization Problem
NSGA	Non-Dominated Sorting Genetic Algorithm
NSGA-II	Elitist Non-Dominated Sorting Genetic Algorithm
PDEA	Pareto Differential Evolution Approach
UML	Unified Modelling Language

ABSTRACT

This dissertation reports on the original study that applies the differential evolution algorithm to support farmers with optimal strategic decision making in the crop planning system. The analysis and modelling of crop planning decision making process are attractive for producing formalized knowledge on cropping plans and choices of farmers under uncertainty. The formalization of the decision making process is generally becoming a crucial focal point for developing decision support systems that go beyond the limitation of formerly developed prescriptive approaches. This dissertation makes a distinctive contribution to the development of a formalized methodology to study the decision making process in crop farming systems. The research reported in this dissertation formulates crop-mix planning problems by concurrently maximizing net profit and crop production, while minimizing the total land in hectare used to determine optimal cropping patterns.

Different optimal crop-mix problems formulated in this research were solved using a mathematical methodology of generalized differential evolution 3 algorithm to obtain globally optimal solutions. The methodology of this research strikes a balance between mathematical formulations of crop planning problems and effective implementation of crop planning decision models. Simulation experiments were conducted using the non-dominated sorted genetic algorithm II to validate the performance of the generalized differential evolution 3 algorithm for solving optimal crop planning problems. The empirical results of this study generally indicate that generalized differential evolution 3 algorithm is a viable alternative for optimal crop-mix planning decision. Based on the performance of the generalized differential evolution 3 algorithm, the design of a decision support system was realized which promises to assist farmers and decision-makers within the agricultural sector to make optimal decisions pertaining to crop planning.

CHAPTER 1

INTRODUCTION

This dissertation proposes a decision support system based on crop mix optimization as an effective way of supporting farmer to optimally plan for available quantity of agricultural input resources. The purpose of agricultural crop planning decision is to guarantee sufficient food resources for the population. The demand for food globally is growing at accelerated rates; most of the current techniques used in expanding agriculture have serious long-term implication for the environment (Tilman *et al.* 2011). The impact of increasing crop demand definitely depend on the development of global agriculture. Development of the agricultural farming system is directed toward achieving great technology improvement and meeting the year 2050 crop demand with much lower environmental impact. The impact of doubling global crop production will depend on how increased production is achieved (Gray *et al.* 2009). Intensifying agricultural practices such as clearing additional land for crop production, achieving higher yields through increased inputs and other innovations could increase crop production and promote agricultural value chain (Tilman *et al.* 2002).

The agricultural sector is considered to be a strategic domain when it comes to the subsistence, survival, development and re-launching of the economy as it has a relative importance in terms of job creation and future growth of the population (Santo 2013). The economic growth of most countries is a factor of the failure or success of agriculture. In South Africa, the percentage of GDP in agriculture has decreased over the past four decades (Media-Club 2007). This decrease has caused a negative trend on the GDP and signaled that there is need to pay more attention to the agricultural sector. Without any hesitation, agriculture is therefore essential to societal development and economic growth in developing countries where the entire benefit, success and farming fortunes are proximately related.

Enormous portions of the population are habitants of the rural communities in most developing countries; therefore in any endeavor to ameliorate the livelihood and income of the poor, the research community cannot neglect the paramount role of the agricultural sector (Perret *et al.* 2005). For decades, important investment in technological development in agriculture has led to the intensification of productivity of farmers in Africa. Hence, despite the effort, micro-level farm output and productivity have remained stagnated and poverty rates have remained high and even increased in some regions (Vink and Kirsten 2003). Homogeneous to further changes occurring at the different levels of the whole society, agriculture is facing incipient challenges. The rising environmental concerns (Duraiappah *et al.* 2005) and possibility of changes in climate (Richardson *et al.* 2009) necessitate the adoption of incipient farming practices to meet challenges of the future (McIntyre *et al.* 2009). In parallel to this, the increasing growth in human population has caused an increase in demand for food resources as well as for arable acreage.

The growing increase of farming system has been complemented by degradation of wild acres of land, including tropical forests and wet-land, at an alarming rate. Additional pressure on fragile land resulting from population growth and urbanization has made the conversion of agricultural land to residential and industrial uses with solemn consequences for agricultural production and food supply, thereby reducing the amount of land available for agricultural purpose. This scenario is being described in most of the developing countries including South Africa. The rapid population growth and reduction in arable land are ostensibly becoming a phenomenon in developing countries. The farmer's socioeconomic perspective is transmuting as a result of the high fluctuating in crop prices coalesced with the incipient rule and regulations in agriculture. In a broader perspective, most farming systems are extremely exposed to the three risk sources in agriculture: market, production and institutional risk (Hardaker 2004). These elements query the impotency of the present farming systems and more so the reasons for their adaptive capacity to face the ever changing environment (Brooks *et al.* 2005; Smit and Wandel 2006; Darnhofer *et al.* 2011)

Agriculture is expected to meet the food demand of the world population that is expected to grow from approximately 6 billion in 1999 to between 8 and 11 billion by 2050 (USDA 2008), this basically ascertains an increase in demand for plant and animal products that are produced (FAO 2009). In line with the increasing demand for agricultural produce, farming systems are not able to absorb and cater for the increasing demand (Liapis 2011). Every farm is an intricate system of interacting components that subsists in both natural and socioeconomic environments (USDA 2008). Balancing of the environmental efficiency and production sustainability, a high management skills and knowledge are essential.

The difficulty of making decisions to ascertain financial survival and growth has increased enormously because the highly dynamic agricultural environment in which farmers have to operate. In order to ensure the financial survival and growth of the agricultural farm, decision in terms of production, procurement, merchandising and financial management is necessary to be accepted by farmers. Hence, taking these decisions as to attain the set goals and objectives with a highly dynamic and diverse environment is very difficult and in many instances virtually invisible. In terms of different approaches, processes and methods, the field of making decisions or analyzing decision offers a wide range of options to facilitate more preponderant decision-making. Modelling forms part of these methods and procedures to facilitate more preponderant decision-making through better understanding of the influence of exogenous and/or endogenous change. Several types of models on farm level can help to improve the understanding of different agricultural systems on a micro and macro levels. A better understanding of the different agricultural systems is likely to contribute to enhanced understanding of the underlying dynamic and risk inherent in each system and subsystem, thereby improving decision-making with regards to business strategies and government policies.

1.1. Problem statement

Efforts to raise agricultural productivity in the farming systems of the developing countries have dominated recent interventions of policies (FAO 2009; Steve and Henri 2010). In South Africa for instance, several programmes have been introduced by the government to increase the productivity of small scale farms that now have to compete with the commercial farms which have always been able to survive the harsh past and the current socioeconomic environment (NDAS 2001). The increasing environmental trepidations (Dobbs and Pretty 2004) and possibility of change in climate (Pachauri 2008) makes it necessary to adopt proactive decision making farming practices to meet challenges of the future (FAO 1997; Dury *et al.* 2010; Montazar and Snyder 2012). The difficulty of making good decision with regards to "what to plant" and "how to allocate the right area of land for the appropriate crop" increase significantly within a highly dynamic environment. In addition, farmers and decision makers within the South African agricultural sector lack access to farming tools and resources that could assist them in optimizing crop making plans (NDAS 2001; AGER 2002).

This study proposes the following research question "how can farmers provide crop production plans, which determine the areas of land to be utilized for several crops, while meeting the demand, acreage and resource limitations?"

1.2. Study rationale

Year after year, farmers have to allocate their acres of land to different crops based on their various crop planning decision options. However, these decisions are difficult and could have considerable effects on farm profitability, efficiency and productivity in the short, the medium and the long-run (Dogliotti *et al.* 2004; Dury *et al.* 2012). Considering that land utilization decisions are core decisions occurring at the farm levels, these decisions are essential to crop planning and have a high impact on efficient utilization of farm resources. The rationale behind this study are as follows:

a. Modelling of crop planning problems and making optimal strategic decisions in crop farming system is an important phenomenon to boost agricultural productivity.
b. Producing knowledge on the possible alternative ways to help farmers choose their crop planning strategies in irrigated arable farms and to support farmers in their annual and long-term joint crop planning and land allocation strategies is an important process to strengthen the capacity of local farmers.
c. Contributing to the research on crop planning and crop rotation decisions has been integrated into optimization modelling.

1.3. Study methodology

The optimization technique employed in this dissertation is called generalized differential evolution 3 (GDE3). The GDE algorithm is an extension of differential evolution (DE) algorithm for optimization with several objectives and constraints (Kukkonen and Lampinen 2005b). Studies on multi-objective evolutionary algorithms and multi-objective optimization has been very active during the last two decades. These studies have concentrated on developing new multi-objective evolutionary algorithms in order to find good solutions set as possible. Differential Evolution (DE) is a relatively new evolutionary algorithm and has been gaining popularity in recent years because of its simplicity and good observed performance. Several extensions of DE for multi-objective optimization have already been proposed.

The older optimization approaches just convert a multiobjective optimization to a single-objective problem and use DE to solve the single-objective problem (Babu and Jehan 2003), whereas more recent and advanced approaches mainly use the concept of Pareto-dominance (Mezura-Montes *et al.* 2008). GDE3 improves earlier GDE versions in the case of multi-objective problems by presenting a better distributed solution (Kukkonen and Lampinen 2006). The performances of GDE3 have been tested by different authors (e.g. Kukkonen and Lampinen 2005b; Einstein 2012) using multi-objective test problems and it was deduced that GDE3 provides better distribution of solutions than the earlier GDE versions and is also more robust in terms of the selection of the control parameter values. In addition GDE3 uses the concept of Pareto-dominance to find its solutions. In parallel to these advantages, this study applies GDE3 support farmers with optimal strategic decision making in the crop planning system.

1.4. Study objectives

This dissertation concerns the modelling of crop-mix planning as constrained multi-objective optimization problems of concurrently maximizing total profits, total crop production and minimizing land utilization and their solutions using an evolutionary metaheuristic algorithm. The originality of this study lies in the formulation and use of a state-of-art an evolutionary metaheuristic algorithm, which has never been used to solve crop planning problem as reported in this dissertation. In addition, designing a practical decision support tool predicated on an evolutionary metaheuristic algorithm that could assist in optimal crop planning decision making. The objectives of the research are:

a. Formulate a realistic crop planning decision task as a constrained multi-objective optimization model,
b. Apply the generalized differential evolution algorithm for optimal crop planning decision making
c. Apply generalized differential evolution algorithm to determine the optimum cropping pattern that will generate the maximum profit for farmers
d. Validate the performance of generalized differential evolution algorithm
e. Implement a prototype decision support system using generalized differential evolution algorithm.

1.5. Study scope

The scope of the study is limited to addressing the issue of crop planning decision making in irrigated arable farms. Farmers are often confronted with planning challenges due to the cyclical nature of agricultural product prices. When prices of crops are low, it results in small margins, crop planning is increasingly significant as farm managers and agricultural policy maker strive to maximize the farm's net profit. Determining the appropriate crops to grow and the area of land suitable for planting each crop are complex planning decisions. Each year, farmers go through a process of determining which crops to plant on each plot and such decisions are made on a crop pattern basis or on a plot by plot basis. If a farmer utilizes the cropping pattern concept, the farmer may cull out several cropping patterns and then decide which plots should be in each crop rotation. The decision as to which pattern should be utilized in each plot will be dependent on several factors. Conventionally, this points to the fact that the process for making cropping decisions is essential in crop planning.

1.6. Study contributions

The development of a web-based decision support system based on crop-mix optimization incorporated with a state-of-art-evolutionary algorithm is a unique contribution of this work. This study contributes to the following:

a. Promoting subsistence farming as an attractive alternative to guarantee sufficient food production and reduce the complete reliance of people on government and cooperation to provide food resources.

b. New perspectives for developing farm specific decision support systems that are based on an evolutionary metaheuristic algorithm

c. Development of a formalized and integrated methodology to study and model complex decision-making process.

d. Knowledge of the cropping plan modelling field.

1.7. Study outline

The dissertation consists of six chapters. The first chapter introduces the general background on crop planning, problem statement, as well as the methodology of the study. In particular, Chapter 1.2 outlines the rationale and motivation of the study. The objective of the study is introduced in Chapter 1.4. The scope and potential contributions of the study are discussed in Chapter 1.5 and Chapter 1.6 respectively. The remainder of this dissertation is structured as follows.

Chapter 2 is a review of more than 150 references in which the concept of crop planning and crop rotation decisions have been integrated into models inclusive of reference in which the concept of evolutionary algorithms have been applied. The intention was to review how crop planning and crop rotation concepts have been used in economic, agronomic and land use studies. This Chapter shows that the modelling of crop planning has been treated with varieties of techniques, predicated on different objectives and solved for different farm scales. The crop planning models were based primarily on two important concepts, crop planning and crop rotation selections. It was argued that decisions concerning crop planning and crop rotation are part of the same decision-making process because they are the essence of the cropping systems design at the farm scale. However, these decisions are not the only single decision but processes incorporated dynamically into a series of other planned and adaptive decisions made on annually or a long-term basis. To support farmers in their decisions, a decision support tool with a new crop planning decision model is needed. This chapter also discusses an evolutionary algorithm and its approaches.

Chapter 3 describes the research methodology of this dissertation. This chapter presents different development phases of Generalized Differential Evolution (GDE). The Chapter also unpacks the theoretical frameworks that guided the research and how the GDE3 methodology was followed in designing the system. Chapter 4 presents the performance comparison of GDE3 with NSGA-II for solving the crop-mix planning model. Chapter 5 presents the implementation of the crop planning decision support system and its various components. The chapter provides the systematic documentation of the research design and holistic approach that is followed in designing the decision support system for the crop planning problem The chapter provides the insight on how the crop planning web application works. Chapter 6 concludes the dissertation. Limitations of the study and recommendation for future work are also presented.

1.8. Publications

This work has resulted in the development of a crop planning system artefact and the following research publications are published or submitted to peer-reviewed journals and conference proceedings.

a. **Journal articles**
   i. Adekanmbi, O., Olugbara, O. and Adeyemo, J. 2014. An Investigation of Generalized Differential Evolution Metaheuristic for Multiobjective Optimal Crop-Mix Planning Decision. *The Scientific World Journal*, 2014.
   ii. Adekanmbi, O. A., Olugbara, O. O. and Adeyemo, J. 2014. A Comparative study of State-of-the-Art Evolutionary Multi-Objective

Algorithms for Optimal Crop-mix planning. *International Journal of Agricultural Science and Technology (IJAST)*, vol. 2, no.1, pp. 8-16.

iii. Adekanmbi, O. A. and Green, PE. 2014. A Meta-Heuristics Based Decision Support System for Optimal Crop Planning. *Mediterranean Journal of Social Sciences*, vol. 5, no.17.

iv. Adekanmbi, O. A. and Olugbara, O. O. 2013. A constrained multi-objective crop-mix planning problem using generalized differential evolution. *Journal of Agricultural Science and Technology*. (Accepted)

v. Adekanmbi, O. A., Olugbara, O. O. and Adeyemo, J. A. Performance of Generalized Differential Evolution Algorithm for Optimal Crop-Mix Planning. *International Journal of Computational Methods*. (Submitted)

b. **Conference proceedings**

i. Adekanmbi, O. A. and Olugbara, O. O. 2013. A system to assist subsistence farmers in optimal crop planning decision. In: Proceedings of *Urban Agriculture: A Growing Field of Research Workshop at INTERACT 2013 – 14th IFIP TC13 Conference on Human Computer Interaction.* Cape Town, South Africa, September, 2013. INTERACT, 45-53.

CHAPTER 2

LITERATURE REVIEW

The agricultural sector is generally being faced with the problem of water use, soil erosion, biodiversity and landscape design (Tong and Chen 2002; Verburg *et al.* 2002; Rounsevell *et al.* 2003). Climate change (Pachauri 2008; Richardson *et al.* 2009), market variation and regulation amendment for more sustainable resource planning compel farmers to perpetually adopt new farm practices. The adoption of these new farm practices aims to address issues relating to efficient use of resources and economic sustainability (Landais 1998; Meynard *et al.* 2001). The farmer's acceptance of crop planning which is a key concept for designing an innovative cropping system is an illustration of the adoption of the new farm practices (Studdert 2000; Bachinger and Zander 2007; Castellazzi *et al.* 2008). Furthermore, with the success rate of crop planning, leading researchers are requesting for new farm practices on which the developments of the new systems will be based (Van Notten *et al.* 2003).

Considering the difficulty of farming systems, model-based exploration tool is commonly utilized to complement the traditional empirical techniques (Vereijken 1997) for evaluating and designing new agricultural production systems. In spite of being faced with various challenges in transferring results to farmers (Keating and McCown 2001; Keating *et al.* 2003; Stöckle *et al.* 2003), the suitability of a model-based techniques has been proved (Rossing *et al.* 2007). Crop selection and their land allocation are essential in crop planning decision making. These decisions focus on the complexity involved in the design of an innovative cropping system and selection of cropping plans which occurs at different stages of crop production (Navarrete and Le Bail 2007; Dury *et al.* 2012).

In crop production processes, crop planning decisions are certainly crucial with consequential influence on the long-run profitability and annual productivity of farms. A suitable crop planning model must satisfy several conflicting objectives and considering various factors/constraints and their interactions (Nevo and Amir 1991; Mohan and Arumugam 1997; Ganesan 2006). Several models incorporated with designing a crop planning system have been built on cropping plan selections which could be the selection of either crop rotation or crop planning. The concept (crop rotation and crop planning) describes the crop planning decision problem in time and space respectively. Not all models studied were developed to support cropping decisions. Nevertheless, most of the models support the selection of one or more cropping plans within a specified objective. In order to avoid any mix-up, *crop planning selection models* have been utilized as a general term to designate the models reviewed. The c*rop planning decision model* was used by the authors when referring to the decision-maker behaviour.

The modelling of crop planning, selection has been modelled using various methods which are based on several objectives. On this topic, more than 100 scientific literatures have been found. This chapter surveys how crop planning and crop rotation concepts have been developed and integrated into economic and land utilization models. The first section discusses the concept of making decisions in crop planning and explains the terminology. The second section surveys crop planning selection models by focusing on arable land and categorize the why and how of the models. The effects of the dynamic features of current methods, including their weaknesses are discussed in the second section. The third section discusses the concept/working principle of evolutionary algorithm and provides brief background information into multi-objective evolutionary algorithm. The section reviews the real world application where evolutionary algorithms have been adopted and discusses how the performances of evolutionary algorithms are being measured.

2.1. Definition, Terminology and Conception

The author opted to explain the definitions and terminology used in crop planning, crop rotation and other related concepts before reviewing the modelling methods incorporated with cropping plan selection or any related topics. Elucidation is not only used when defining the meaning of words, but also for describing, specifying understanding, identifying and realizing the significance of using some concepts in crop planning models.

2.1.1. Crop planning

Crop planning is the engagement of land by planting several crops every year and their spacial dispersion in the allocated farmland (Wijnands *et al.* 1999). In that context, the definition of crop planning includes two widely used concepts on land utilization and crop planning (Figure 1). Firstly, crop land, is the farming land area usually assigned to the cultivating of several crop groups every year. Secondly, crop allocation, refers to the distribution of a specific crop to each piece of land for cultivation. Allocation of land for specific crop can be spatially explicit (Joannon *et al.* 2006; Sethi *et al.* 2006; Belfares *et al.* 2007) or can be characterized by the attributes of a land area such as soil type (Romero and Rehman 1984; Siegfried *et al.* 2009; Bergez *et al.* 2010). In a farming system, the crop planning stage can be expressed as the stage where the majority of the decisions are made (e.g. Bachinger and Zander 2007).

(a) (b)

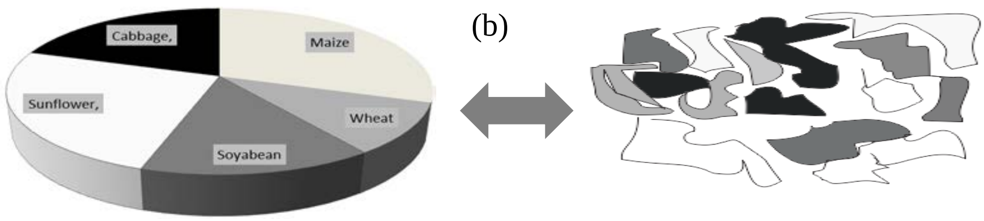

Figure 1: (a) Crop acreage can be simplified as the crop area distribution, represented here by means of a pie chart, while (b) crop allocation calls for the clear representation of land units, on a map for instance, or their characterization in terms of various land attributes (Dury *et al.* 2012).

2.1.2. Decisions in crop planning

Crop planning decisions are important in the utilization of land in a farming system and involve the selection of crops to be planted and their land allocation within a specific arable land (Nevo *et al.* 1994; Aubry *et al.* 1998a). These strategic decisions take place at the farm level, and are therefore part of the activities that occurs on the farm (Dury *et al.* 2012). A crop planning decision is the outcome of a decision making process where farmers consider several objectives and constraints. When farmers are making crop planning decisions, the primary concern is economics/profit. However, once the crops that will provide the highest net profit have been determined, they will often consider rotations, herbicide residues, weed quandaries and several other factors. This occurs as a result of the uncertainties that surrounds the decision-making process in that there may be various planting seasons, crop planning decision making does not only include a single decision but a continuous approach taking place all over the year (Aubry *et al.* 1998b; Johnson and Morehart 2006; Nuthall 2006).

2.1.3. Crop rotation

Crop rotation is referred to as the process of cultivating different kinds of crop in succession on the same piece of land rather than employing a one-crop system or variety of crops (Bullock 1992; Stone *et al.* 1992; Studdert 2000). In the rotation system, crops are alternated on the substratum of the amounts and types of organic matter that each crop returns to the soil and characterized in succession while the crop sequence is limited to the order of appearance of crops on the same piece of land during a set time (Liebig *et al.* 2002). The process of rotating crops is a concept often employed in models to represent the time-based attribute of crop planning decisions (Pacini *et al.* 2004; Janssen and van Ittersum 2007). Due to crop succession in a given region, crop production is affected which afterward affects crop planning decisions. The conventional method developed by agronomist was used to develop cropping plans from the crop ratios in crop rotation. In some paper, the authors (Dogliotti *et al.* 2003; Morlon and Trouche 2005) argued that the choices of crop are obtained from crop rotation, and it can be used to ascertain the reproducibility of a cropping system over a period of time.

Crop planning decisions require proper consideration of the decisions before the selection (Figure 1). To design suitable cropping systems, crop rotation is considered to be the natural starting point (Vereijken 1997), it is also being regarded as important to be incorporated in crop farming (Wijnands *et al.* 1999; Stoate *et al.* 2001). It has a different view when compared with mono-cropping and considered as a viable solution for crop farming (Dunin *et al.* 2001). The crop rotation concept is a way of obtaining crop succession annually on a given land. Crop rotation proposes the possibility of reducing the environmental impacts of agriculture and at the same time sustaining crop production (Swift and Ingram 1996; Altieri and Nicholls 2004). The concept is also utilized for reducing dependence on external inputs, breaking disease and weed cycles (Bullock 1992).

2.2. Reasons for modelling crop planning

Given the large range of effects of the crop planning decisions at the farm level, the designing of cropping plans using models is driven by many different motivations (Dury *et al.* 2010). Crop planning models are generally utilized to help agricultural policy maker, and farmers, in defining important strategies to evaluate landscape changes, allocate scarce resources efficiently. Several research was carried out using crop planning models, it was observed that these models share similar result when separately used within different research projects (Matthews *et al.* 2011) to meet different objectives (Alexandrov *et al.* 2011). Crop planning models were not only reviewed in terms of outcomes of projects but rather on how they affect the selection of cropping plan. Several methods have been summarized as two broad issues:

i. Crop planning selection for more improve resource allocation and more efficient resource utilization, and

ii. Crop planning decisions to evaluate large-scale changes (that is changes involving crop policy and landscape).

Even though, this distinction is important for presenting the existing works on crop planning, the researcher acknowledges that there is in fact strong relationship between the two issues.

2.2.1. Crop planning problem formulation

Crop planning models are usually developed to obtain better techniques of performing the resource allocation and land utilization. The techniques help to explore and design an alternate land-utilization system at several farm levels and may help in identifying best crop combinations and resource allocation choices

(Dury *et al.* 2012). The primary goal of these models is to assist farmers and others in making strategic decisions while designing the farming systems. The modelling of a crop planning problem requires proper illustration and representation of the selection process in crop planning. The detailed level representation of the design process depends greatly on the objectives of the study. Formulation of crop planning problems is usually represented in models as a deterministic and a static resource allocation problem and is usually treated as the search of the appropriate land for the best crop combination under some constraints. In most crop planning models, the decision process is characterized as a single decision occurring in (i) once a rotation or (ii) once a year:

i. Numerous studies indicate that the selection process in crop planning is directly obtained from the selection process in crop rotation which mostly is used as the main concept in the cropping system designs. The transition of crop rotations to crop planning models is frequently predicated on agricultural expert's knowledge using several crop sequence representations (Table 1). Computed crop rotation (Detlefsen 2004; Bachinger and Zander 2007) or recommended crop rotations (Stöckle *et al.* 2003) considers crop sequence requirements when selecting crop production plans (Dunin *et al.* 2001; Haneveld and Stegeman 2005). Several authors (Streit *et al.* 2003; Leteinturier *et al.* 2006) have demonstrated that annual flexibility in crop rotations improves the outcome of static crop rotation. Dogliotti *et al.* (2003) described flexible crop rotations to be of three types of:

a. fixed cyclic rotation,
b. variable cyclic rotation and
c. high variable rotation with less cyclic structure.

Several numerical formulation has been employed to represent flexible crop rotations in models, for instance Markov chains (Castellazzi *et al.* 2008) and network flow problems (Haneveld and Stegeman 2005; Leteinturier *et al.* 2006; Detlefsen and Jensen 2007). The benefit of incorporating flexible crop rotation into crop planning models is the ability to represent annual adjustment in cropping plans (Dury *et al.* 2012).

ii. In crop planning related researches where selection processes are made on a yearly basis, the crop sequence requirements are either overlooked (Jones 1992; van Berlo 1993; Bergez *et al.* 2001) or integrated into the models as parameter for reducing crop produce (Haneveld and Stegeman 2005; Chabrier *et al.* 2007). Crop produce reduction parameters are either set by farm specialists (Stöckle *et al.* 2003) or built on the regression exploration of historical information (Detlefsen 2004), and as a result, selection process in crop planning is viewed as a single static decision of resource allocation (Dury *et al.* 2012). None of these methods consider a series of decisions in their problem formulation. Farmer's behaviour towards risk are always poor taking into account the uncertainties in some information (such as price and weather). The aspects of behavioural responses towards risk are studied in details in the field of agricultural economics (see: Wu 1999; Lien and Hardaker 2001; Itoh *et al.* 2003; Hardaker 2004; Olarinde *et al.* 2008).

Table 1: Representation of crop sequence in crop planning models predicated on the rotational method

	Crop sequence requirements	**Authors**
Crop sequence predefined by experts		Stöckle *et al.* (2003); Sadok *et al.* (2009b)
Crop sequence based on guidelines	Rules governed by the users of the models with parameters that define sequence, timing and specific farm constraints.	Dogliotti *et al.* (2003); Streit *et al.* (2003)
	Predefined crop succession.	Liebig *et al.* (2002); Haneveld and Stegeman 2005
	Crop demand and supply constraints, omission rules.	Streit *et al.* (2003)
	Predefined allowed crop sequences	Dunin *et al.* (2001); Hao *et al.* (2001)
Crop sequence based indicators	Impacts of preceding crops on the successive crop and their corresponding	Leteinturier *et al.* (2006)

	crop diversity, minimal return time.	
Crop sequence based on the probability of crop occurrence	Probabilities predicated on practical crop rotations.	Castellazzi *et al.* (2008)
Crop sequence based on reducing factors	A regression study to assess the impact of previous crop on production	El-Nazer and McCarl 1986
	Scheduling and sequencing constraints, production reduction penalties associated with disease classes	Annetts and Audsley 2002
	Predefined production reducing factors	Garcia *et al.* (2005); Chabrier *et al.* (2007)

2.2.2. Crop planning problem resolution methods

2.2.2.1. Optimization

Several techniques have been used to solve crop planning problems while satisfying the operational constraints. To a great extent, mathematical programming has been extensively utilized in this area (Belegundu and Arora 1985; Glen 1987; Feiring *et al.* 1998). Linear programming is the most popular optimization approach since Heady (1954) that has been employed in solving crop planning decision problems (Hazell and Norton 1986; Mainuddin *et al.* 1997; Sarker *et al.* 1997; Adeyemo and Otieno 2009). The linear programming model gained its popularity because of its simplicity and its ability of solving selection problem with various objectives (Leroy and Jacquin 1991). Some of the problems associated with the use of this method take account of the difficulties in formulating the problem's objectives, constraints and deducing its results (Buick *et al.* 1992). The original linear programming framework has been extended in several application areas to reduce its limitations (Adeyemo and Otieno 2009). Simple optimization approaches have been improved in several ways by searching for optimal solutions (Olarinde *et al.* 2008; Sadok *et al.* 2009a), by incorporating fuzzy logic methods in order to ascertain the qualitative factors

(Nevo *et al.* 1994), and decision's flexibility (Itoh *et al.* 2003) and random variables to address the uncertain factors (Sethi *et al.* 2006).

Multi-objective linear programming or Goal programming is an extension of linear programming models which is used to solve crop planning problem formulated as a multi-objective crop planning problem (Annetts and Audsley 2002; Biswas and Pal 2005; Sahoo *et al.* 2006; Sharma and Jana 2009). Based on the study, several objectives are clearly formulated with multi-dimensional function inside the crop planning models (Table 2). For example, Sarker and Quaddus (2002) developed a goal programming model taking into account a wide range of farming situations, and allow optimization of environmental and/or profit outcomes. A multi-objective linear programming model was developed by Annetts and Audsley in 2002 for environmental farm planning (Annetts and Audsley 2002). The multi-objective linear programming model was predicated on the crop planning model in Audsley (1993). The optimization tool provided an insight and helps to find out if a reduction in environmental impacts is achievable with minimal reduction in profit. Hayashi (2000) presented a comprehensive analysis of their application to agricultural resource management. Several multi-criteria methods have been employed in crop planning models by combining several objectives.

The main challenge of the multi-criteria techniques is in their ability to extract the objectives and elicit constraints, and thereafter assign weights to each objective using different weighting coefficient (Sumpsi *et al.* 1997). The linear programming framework is used not solely on almanac problem but for solving the crop planning problem. Haneveld and Stegeman (2005) utilize a standardized linear programming model integrated with a max-flow network representing the crop successions and predefined crop sequences that are not acceptable from an expert viewpoint are used as constraints. Detlefsen and Jensen (2007) used a network modelling technique in a slightly different way to model the problem of finding an optimal crop rotation for a given crop selection on a particular piece of land. Both approaches permit the application of flexible crop rotations in view of crop sequence requirements. Dogliotti *et al.* (2005) developed an interactive multiple-goal linear program named as “Farm Images” using mixed integer linear programming to solve the crop rotation problem. The approach was used to apportion production activities to a unit of farm lands of different soil quality, aimed at maximizing or minimizing socioeconomic and environmental objectives. The originality of the approach is that both the spatial heterogeneity of soil types of the farmland and the complex temporal interactions of rotation are considered in solving the crop planning problem.

Lately, evolutionary optimization algorithms have been employed in addressing multi-objective crop planning problem at the farm level (Brunelli and von Lücken 2009), at a nationwide level (Sarker and Ray 2009) and provincial scale (DeVoil *et al.* 2006). The advantage of using evolutionary optimization algorithms is to get a set of solutions obtained from a set of Pareto optimal solution (Coello 2009). Such algorithms seem particularly desirable for obtaining solutions for multi-objective optimization problem. Though, evolutionary optimization algorithms are quite different from linear programming methods, the formulation of the crop planning problem using an evolutionary optimization algorithm is closely related to the way crop planning problems are treated using other mathematical techniques. Heckelei and Britz (2005) and Louhichi *et al.* (2010), propose a nonlinear optimization approach predicated on positive mathematical programming (PMP). PMP employs both programming constraints and "positive" inferences from base-year crop allocations.

Table 2: Objectives clearly formulated in crop planning models [↑: maximization, ↓: minimization].

Categories	**Objectives**	**Indicators**	**Authors**
Agronomy	Irrigation	↑: irrigated area	Mainuddin *et al.* (1997); Feiring *et al.* (1998); Gupta *et al.* (2000); Bergez *et al.* (2001); Tsakiris and Spiliotis 2006; Adeyemo and Otieno 2010a
Socioeconomic	Profit	↑: annual profit, gross	Piech and Rehman 1993; Nevo *et al.* (1994); Foltz *et al.* (1995);

		margin, net benefit, income	Mainuddin *et al.* (1997); Abdulkadri and Ajibefun 1998; Gupta *et al.* (2000); Sarker and Quaddus 2002; Dogliotti *et al.* (2005); Tsakiris and Spiliotis 2006; Sarker and Ray 2009; Adeyemo and Otieno 2010a; Louhichi *et al.* (2010)
	Labour	↓: cost, casual labour, total labour	Piech and Rehman 1993; Gupta *et al.* (2000); Dogliotti *et al.* (2005); Bartolini *et al.* (2007); Sarker and Ray 2009
Environment	Energy	↓: calories	Gupta *et al.* (2000)
	Nutrient	↓: phosphorus and nitrogen uses	Foltz *et al.* (1995); Aubry *et al.* (1998b); Annetts and Audsley 2002; Keating *et al.* (2003); Dogliotti *et al.* (2005)
	Pesticide	↓:pesticide exposures, herbicide use,	Foltz *et al.* (1995); Aubry *et al.* (1998b); Annetts and Audsley 2002; Keating *et al.* (2003); Dogliotti *et al.* (2005)

2.2.2.2. Expert applications

Certain authors (Stone *et al.* 1992; Nevo *et al.* 1994) have indicated that applying only deterministic and quantifiable approaches is not sufficient to realize suitable crop planning due to the type of facts needed; as such facts is frequently uncertain, qualitative and incomplete. Nevo *et al.* (1994) incorporated an expert system technology with a traditional linear and mathematical programming technique to provide a solution to these setbacks. This method provides some consistency in search space pruning, thereby decreasing the number of alternative allocations. These applications also involve a series of fine-tuning procedures that support the measurement of the influence of actual production conditions on the accrued income during a cropping period. The rules are predicated on expert's knowledge and are logically quantified using fuzzy logic techniques and uncertain processes using Bayesian theory. Buick *et al.* (1992) and Stone *et al.* (1992) used artificial intelligence to solve the crop planning problem, not using traditional optimization methods (Dury *et al.* 2012).

2.2.2.3. Evaluation technique

An alternative method for the handling of the crop planning problem is evaluating the alternate crop planning based on indicators, instead than simply choosing one solution. With the help of multi-criteria decision approaches, it is possible to consider the conflicting objectives implicit in the environment, and economic dimensions of sustainability (Sadok *et al.* 2009a). Bachinger and Zander (2007) devised a stable rule-based model, called "ROTOR" to evaluate, generate site-specific and sustainable crop rotations for farming systems. The selection of crop rotation is based on exclusion principles and ranking of their economic performance. Foltz *et al.* (1995) adopted the use of simulation models to derive the values for evaluating indicators such as profitability and environmental quality, and then choose the most suitable cropping plans using multi-attribute ranking.

2.3. Evolutionary Algorithms

An evolutionary algorithm is a general term for a population-based approach and in which is apportioned at the same time with a set (known as population) of solutions that allows to find an entire set of Pareto optimal solution in a single run of the algorithm, instead of working with a single solution have to perform a series of separate runs as in the case of the conventional mathematical programming methods (Coello 1999; Einstein 2012). They are computer programs inspired by the mechanism of natural ability to evolve living being well adapted to their environment (Van Veldhuizen and Lamont 2000) and attempt to solve complex problems by imitating the Darwinian evolution processes (Jones 1998). Evolutionary algorithms consist of such conventional approaches as evolution strategies (Beyer 2001), evolutionary programming (Yao *et al.* 1999), genetic programming (Banzhaf *et al.* 1997), and genetic algorithms (Goldberg 1989). Over the last few decades, evolutionary algorithms have propagated and become more imperative, they have gained much attention in terms of their potential as a global optimization technique.

Prominent recent evolutionary algorithms include particle swarm optimization (PSO) (Kennedy 2010), ant colony optimization (ACO) (Dorigo and Birattari 2010), and differential evolution (DE) (Price *et al.* 2005). Multi-objective optimization literally entails optimizing more than one objective at the same time. The main reasons for the popular acceptance of evolutionary algorithms are that they require no derivative information; they are robust, flexible and relatively simple to implement. Nevertheless, the bottlenecks of working with a population-based approach are the cost of computation and the memory required for the execution of a single iteration (Guliashki *et al.* 2009).

Many real-world problems have multiple objectives and various factors resulting to become constraints to problems. For example, mechanical design problems may have various objectives such as manufacturing costs, obtained performance, and available resources may be limited. The constraints can be categorized into constraint functions and boundary constraints. The constraint functions represent more complex constraints, therefore are expressed as functions becoming a part of an inequality equation (Einstein 2012). Boundary constraints are utilized when the decision variable value is restricted to some range. Constraint handling will not be reviewed in this section as constraint handling has not been developed in this work.

2.3.1. Multi-objective evolutionary algorithms

Multi-objective evolutionary algorithms (MOEAs) are designed to solve multi-objective problems. Originally, evolutionary algorithms were used in connection with approaches that utilized aggregating function, such as ε-constraint method, value function method, weighted metric methods, goal programming method, and weighted sum methods (Zhou *et al.* 2011). But as a result, multi-objective optimization problems are treated by combining all objectives into a single objective which either makes use of a multiplication or addition function, or formulate any other arithmetic operation, which thereafter solves the problem using single-objective evolutionary algorithms (Coello *et al.* 2007).

More recently, a Pareto-based evolutionary algorithm approaches started to emerge and gain acceptance due to the ability of evolutionary algorithm to easily provide a set of candidate solution, a feature that is desirable in a Pareto-based multi-objective optimization (Einstein 2012). In general, multi-objective evolutionary algorithms are considered as Pareto-based method, i.e. their goal is to locate a limited number of well converged and distributed solutions (Coello *et al.* 2007; Einstein 2012). Recent academic literature contains hundreds of references about multi-objective evolutionary algorithms, including hundreds of doctoral theses (Coello 2012). Distinguished doctoral theses about multi-objective evolutionary algorithms were completed by da Fonseca (1995), and Veldhuizen (1999). Several books about multi-objective evolutionary algorithms are also available. The most prominent books are written by Coello *et al.* (2007) and Deb *et al.* (2005).

2.3.2. Applications of multi-objective evolutionary algorithms

Real-world optimization problems are much too difficult to be solved through analytical means. Multi-objective evolutionary algorithms, a family of algorithms that use the mechanism of naturalistic evolution, are suitable for solving such problems. These algorithms are stochastic methods of optimization, they are effective, involve no derivative, robust and are not faced with the challenge of being stuck in local minima; they are proven to work well for several complex optimization problems (Das and Panigrahi 2009). Conventionally, evolutionary algorithms have concentrated on optimizing single objective functions, researchers from several fields of science and engineering have been applying multi-objective evolutionary algorithms to solve optimization problems originating in their own fields. The literature on multi-objective evolutionary algorithms applications is exceedingly huge and multifaceted. Therefore, only the major applications of multi-objective evolutionary algorithms are summarized in Table 3.

Table 3: Summary of applications of multi-objective evolutionary algorithms to real world problems

Application	Sub-Application areas	Authors
Scheduling heuristics	Planning	Rahimi-Vahed *et al.* (2007); Saadatseresht *et al.* (2009); Sarker and Ray 2009
	Scheduling	Hanne and Nickel 2005; Chang *et al.* (2007); Lee *et al.* (2007); Li and Wang 2007; Tavakkoli-Moghaddam *et al.* (2007); Chang *et al.* (2008); Qian *et al.* (2009); Xing *et al.* (2009); Zuo *et al.* (2009)
Rule extraction and data mining	Rule extraction	Ghosh and Nath 2004; Ishibuchi and Yamamoto 2004; Tan *et al.* (2006b); Alatas *et al.* (2008); Gacto *et al.* (2009); Sánchez *et al.* (2009); Chan *et al.* (2010); Zhang and Rockett 2011
	Data mining	Ghosh and Nath 2004; Ishibuchi and Yamamoto 2004; Alatas *et al.* (2008)
Management and assignment	Placement	Ting *et al.* (2009)
	Management	Siegfried *et al.* (2009)
	Resource allocation	Belfares *et al.* (2007)
	Assignment	Toroslu and Arslanoglu 2007; Yang and Chou 2011
	Routing	Lin and Kwok 2006; Tan *et al.* (2006a); Caballero *et al.* (2007); Tan *et al.* (2007); Jozefowiez *et al.* (2008)
	Packing	de Lope and Maravall 2005; Maravall and de Lope 2007; Liu *et al.* (2008)
Circuits and communications	Antenna array design	Panduro *et al.* (2005); Panduro *et al.* (2006); Pal *et al.* (2010)

	Wireless sensor network	Konstantinidis *et al.* (2010); Masazade *et al.* (2010)
	Circuit design	Zhao and Jiao 2006; Chang *et al.* (2007); McConaghy *et al.* (2007); McConaghy *et al.* (2008); McConaghy *et al.* (2011); Mitea *et al.* (2011); Lourenço *et al.* (2013)
	DS-CDMA design	Das *et al.* (2008)
Bioinformatics	Molecular docking	Janson *et al.* (2008)
	DNA sequence design	Shin *et al.* (2002); Shin *et al.* (2005)
	Oligonucleotide probe design	Benedetti *et al.* (2006); Erbas *et al.* (2006)
	Gene network	Koduru *et al.* (2008)
Control robotics and systems	Greenhouse control	Zhang 2008
	Robot motion planning	Osyczka *et al.* (1999); Vadakkepat *et al.* (2000); Nagib and Gharieb 2004; Castillo *et al.* (2007); Garcia *et al.* (2009); Saravanan *et al.* (2009)
	Control scheme design	Aggelogiannaki and Sarimveis 2007
	Controllers design	Silva *et al.* (2008); Woźniak 2011; Zhao *et al.* (2011)
Pattern recognition and image processing	Image processing	Wiegand *et al.* (2004); Balasubramanian *et al.* (2009); Lazzerini *et al.* (2010); Mukhopadhyay and Maulik 2011
	Pattern classification	Handl and Knowles 2007; Romero-Zaliz *et al.* (2008); Mukhopadhyay *et al.* (2009); Ducange *et al.* (2010)
Artificial neural networks (ANNs) and	Neural network training	Pettersson *et al.* (2007); Qasem and Shamsuddin 2011
	Fuzzy	González *et al.* (2006); Aguilar-

fuzzy systems		Lasserre *et al.* (2007); Aguilar-Lasserre *et al.* (2009); Cococcioni *et al.* (2011)
Manufacturing	Plant design	Omkar *et al.* (2011)
	Production engineering	Weinert *et al.* (2009); Zeng *et al.* (2010)
	Composite components design	Aguilar-Lasserre *et al.* (2007); Aguilar-Lasserre *et al.* (2009)
	Process plant	Govindarajan and Karunanithi 2005
Transportation and Traffic engineering	Traffic engineering	Uhlig 2005
	Transportation	Iniestra and Gutiérrez 2009

2.3.3. Performance measurement in multi-objective optimization

Evaluating and comparing the quality of results for a single-objective optimization problem (SOOP) is significantly less challenging and relatively straightforward than for a multi-objective optimization problem. For SOOP, the researcher validate whether the quality of a specific solution was realized, how much computational feat was required, finally how often such quality was realized (Khare *et al.* 2003; Mohan and Mehrotra 2011). The difference between obtaining solutions can clearly be measured and this measure can be used as a performance metric (Einstein 2012). In contrast, the evaluation and comparison of the quality of results in a multi-objective optimization problem is rendered challenging by the absence of a supreme, simple and generally accepted performance metric (Deb 2001). The main reason is that the output of a multi-objective optimization run is a collection of vectors forming a non-dominated set (Deb 2001). Considering a Pareto-based multi-objective case, the goal is to obtain a set of non-dominated solutions which are as close to the Pareto-optimal front as possible and covers the Pareto-optimal front as well as possible (Deb 2001). These two aspects are considered somewhat conflicting, and it has been argued that no single metric can measure the performance of an algorithm (Deb 2001). The following aspects can be used to measure the quality of a result of a multi-objective optimization:

1. Number of non-dominated solutions.
2. Closeness to the Pareto-optimal front.
3. Diversity, which includes:
    a. Distribution of solutions.
    b. Extent of solutions.

The measurement of several different aspects gives more information about the characteristics of a solution set than a single metric value. Several commonly used performance metrics can be found in Deb (2001) and Zitzler *et al.* (2003). In the following, several common performance metrics are briefly covered. Most of them have also been used in the publications included in this dissertation. Metrics for the studies were selected according to the prevailing insight about their suitability to measure certain characteristics. Two commonly used convergence metrics are generational distance and error ratio (Deb 2001), with the former being more often found. For both of these metrics, less is better and the optimal value is zero.

Diversity is also a key consideration. The diversity of the obtained set of solutions has often been measured with spacing, spread, and maximum spread metrics (Deb 2001). For spacing and spread, less is better and the optimal value is zero. For maximum spread, the optimal value is one; if the full spread is not reached then the value is less. The elements of the vector to represent the performance of MOEAs are called the unary quality indicators. Over the past few decades, many unary indicators have been introduced (Table 4).

Table 4: Unary quality indicators

Indicator	Description	Reference
I_{R2}	*R* indicator	Fonseca *et al.* (2005)
I_H^-	Hyper-volume indicator	
I_{HC}	Enclosing hypercube indicator	Zitzler *et al.* (2003)
I_O	Objective vector indicator	
I_I	Unary ε-indicator	

I_P	Number of Pareto points contained	
I_D	Distance from reference set	Esbensen and Kuh 1996
I_{ER}	Error ratio	Veldhuizen 1999
I_{ONVG}	Overall non-dominated vector generated	
I_{GD}	Generational distance	
I_{ME}	Maximum PF error	
I_S	Spacing	Schott 1995
I_{MS}	Maximum spread	Zitzler *et al.* (2003)
I_{MD}	Minimum distance between two solutions	Sayın 2000
I_{CE}	Coverage error	
I_{OS}	Pareto spread	Azarm and Wu 2001
I_A	Accuracy	
I_{CL}	Cluster	

2.4. Conclusions

Agriculture in relation to the environment in which it operates has become increasingly complex due to significant changes that have taken place over the past decades. Due to the increased complexity and interrelatedness, the general optimization approach was adopted in agriculture in order to improve research as well as practical problem-solving in order to improve decision making. This led to the introduction as well as improvement of several different approaches and methods of modelling in agriculture. To take the decision support modelling approaches a step further, the formulation of the cropping plan problem should be carried out within a consultative modelling framework that considers several ways a crop planning problem can be formulated instead of being formulated as a deterministic and static process. Innovative models addressing the issue of crop planning decisions require an incipient modelling paradigm predicated on an optimization process rather than on single prescriptive method.

The modelling of crop planning processes occurring at the farm level needs to clearly consider interactions between a set of constraints of different natures represented in their different time scale. To accomplish this, there is a need for better understanding and formulation of crop planning problems and the determinants of their decisions including risk aversion, for instance price and weather conditions. From the objectives and problem statement of the study, it is clear that the purpose of the study is to create a “tool” that will assist local farmer to make optimal strategic decisions during crop planning. The need to incorporate biophysical and decision models is now recognized as an improvement in farming system design and could be an interesting solution for structuring all the elements that constitute the complexity of the crop planning problem.

CHAPTER 3

METHODOLOGY OF THE STUDY

The methodology employed in this study is two-stages modelling approach. The first stage consists of mathematical modelling of the optimal crop planning problem to execute appropriate algorithms that were in turn used to realize crop planning system artifact. The second stage of the model translates the mathematical specification of a crop planning system into concrete specification while using use case narration to describe the requirements of the system. This chapter discusses the evolutionary algorithm called Generalized Differential Evolution 3 (GDE3) that was applied to solve the crop planning problem, after which a decision support tool was developed. GDE is an extension of DE for optimization with several objectives and constraints. Before discussing more about Generalized Differential Evolution, brief information on DE and its strategies is required.

3.1. Differential evolution algorithm

The DE algorithm (Das and Suganthan 2011), an evolutionary algorithm (EA), and the concept was introduced by Storn and Price in 1995 (Storn and Price 1995; Storn and Price 1996; Storn and Price 1997). The DE algorithm concept originates from the idea of using differences between individuals to mutate another individual. The advantages of differential evolution include efficiency, use of floating point encoding and simplicity (Storn and Price 1995). DE is characterized by self-adaptivity, linear scalability (i.e., the computational cost of the algorithm increases linearly with the number of decision variables) and ability to achieve a rotational constant search. Although DE uses real-coding of variables in its genetic operations, it can be used to solve problems with different types of variables by just a simple conversion to the actual variable types prior to evaluation of an objective or constraints (Lampinen and Zelinka 2000; Price *et al.* 2005).

DE has been gaining popularity in recent years because of its good performance observed in numerical optimization of practical problems. It has also performed well with a number of test problems (Storn and Price 1996; Rönkkönen *et* *al.* 2005). The 2006 IEEE Congress on Evolutionary Computation (CEC 2006) was the first major conference to arrange a special session dedicated solely to DE, and three years later, the DE special session was the largest in the conference. Several variations of the idea exist and these are referred to as DE strategies (Storn and Price 1997; Kenneth 1999; Price 1999). The following section describes the most used DE strategy such as DE/rand/1/bin.

3.2. Basic differential evolution, DE/rand/1/bin

Basic DE is meant for single-objective optimization without constraints and therefore in this section, the notations are for single-objective optimization. As in a distinctive evolutionary algorithm, the idea in differential evolution is to start with a randomly generated initial population, after which the initial population is ameliorated by mutation, crossover and selection operations. To define a termination condition, a delineated upper limit $G_{\max}$ for the number of generations to be calculated is used. This termination condition is used also with DE in this dissertation.

3.2.1. Population Initialization

In DE, the values obtained for initial population are generally drawn from a uniform distribution. This can be demonstrated as (Kukkonen and Lampinen 2008):

$$
\begin{aligned}
&P_G = \{x_{1,G}, x_{2,G}, \ldots, x_{NP,G}\},\ x_{i,G} = (x_{1,i,G}, x_{2,i,G}, \ldots, x_{D,i,G}) \\
&x_{j,i,0} = x_j^{(lo)} + rand_j[0,1] \cdot \left(x_j^{(hi)} - x_j^{(lo)}\right) \\
&\forall i = 1, 2, \ldots, NP,\quad NP \geq 4,\quad j = 1, 2, \ldots, D.
\end{aligned}
\tag{3.1}
$$

From the expression above, P_G represents a population after G generations (0 is an initial generation), $x_{i,G}$ represents a decision vector of the population, and $rand_j[0,1]$ represents a uniformly distributed random variable in the value range [0,1]. The symbols $x_j^{(hi)}$ and $x_j^{(lo)}$ represent upper and lower bounds parameter in the initialization respectively. The population size is represented by NP and the decision vector's dimension is represented by D.

Firstly, It should be noted that the values of initialization bounds ($x_j^{(lo)},\ x_j^{(hi)}$) can be different from the values of boundary constraints ($x_j^{(lo)},\ x_j^{(hi)}$) in the problem definition. For example, some decision variables might be unbounded in the problem definition, but some lower and upper bounds are still needed to initialize these variables. Secondly, it should also be noted that differential evolution is able to advance the search out of the initialization bounds of the decision variables if this is not restricted.

3.2.2. Crossover and Mutation

A corresponding trial vector $u_{i,G}$ is created when DE passes each decision vector $x_{i,G}$ of the population as presented below (Kukkonen and Lampinen 2008):

$$
\begin{array}{l}
r_1, r_2, r_3 \in \{1, 2, \ldots, NP\}, \\
\text{(randomly selected,} \\
\quad \text{expect mutually different and different from } i\text{)} \\
j_{rand} = \text{round } (rand_i[0,1] \cdot D) \\
\text{for} (\, j = 1;\ j \le D;\ j = j + 1) \\
\{ \\
\quad \text{if } (rand_j[0,1) < CR \vee j == j_{rand}) \\
\qquad u_{j,i,G} = x_{j,r_3,G} + F \cdot \left(x_{j,r_1,G} - x_{j,r_2,G} \right) \\
\quad \text{else} \\
\qquad u_{j,i,G} = x_{j,i,G} \\
\}
\end{array}
\qquad (3.2)
$$

Indices r_1, r_2, and r_3 are reciprocally different and drawn from the set of the population indices. The function **round()** rounds its argument to the nearest integer. Functions $rand_i[0,1]$ and $rand_j[0,1]$ return a random number drawn from the uniform distribution between 0 and 1 for each *i* and *j*. Both CR and F are user definable control parameters for the differential evolution algorithm and which always remain constant during the execution process of the algorithm (Kukkonen and Lampinen 2005b). Parameter CR, controls the crossover procedure, it exemplifies the probability that an element of the trial vector is selected from a linear combination of three randomly selected vectors and not from the old decision vector $x_{i,G}$. The condition $j == j_{rand}$ ensures that at least one element of the trial vector is different compared to the elements of the old vector. The Parameter F represents the scaling factor for the mutation and its value is generally $(0,1+]$ (i.e., greater than 0 and the upper limit is in practice around 1 although there is no hard upper limit). Effectively, CR controls the rotational invariance of the search, and smaller values (e.g., 0.1) are more appropriate with discrete problems while greater values (e.g., 0.9) are for non-discrete problems (Fleetwood 2010).

Control parameter F controls the speed and robustness of the search, that is., a lower value for F increases the convergence rate but also the risk of getting stuck into a local optimum (Price 1999). Parameters NP and CR have a comparable influence on the convergence rate as F (Kenneth 1999; Kukkonen and Lampinen 2006). The difference between two randomly selected vectors $x_{r_1,G} - x_{r_2,G}$ delineates the direction and magnitude of the mutation. When the difference is added to a third randomly selected vector $x_{r_3,G}$, this change corresponds to mutation of this third vector. In DE, the basic idea is that the mutation is self-adaptive to the objective function space and to the current population. At the beginning of the optimization process with DE, the magnitude of mutation is large because vectors in the population are far away from each other in the search space. When the evolution proceeds and the population converge, the magnitude of mutations gets smaller (Kukkonen and Lampinen 2005b).

3.2.3. Selection

The old decision vector $x_{i,G}$ is compared to the trial vector $u_{i,G}$ after each crossover and mutation operation. The trial vector replaces the old vector if the trial vector has an equal or lower objective value. Formally, this can be presented as follows (Kukkonen and Lampinen 2008):

$$x_{i,G+1} = \begin{cases} u_{i,G} & \text{if } f(u_{i,G}) \leq f(x_{i,G}) \\ x_{i,G} & \text{otherwise} \end{cases} \qquad 3.3$$

The average objective value of the population will at no time deteriorate, because the trial vector has equal or lower objective value. Then the trial vector replaces the old vector and differential evolution is an elitist search technique.

3.3. Overall Algorithm

The overall presentation of basic DE (sometimes also referred to as “classic DE”) is presented in Figure 2 (Kenneth 1999). This DE strategy is identified with the notation DE/rand/1/bin. In this notation, 'rand' indicates how the vector for mutation is selected. The number of vector differences used in the mutation is indicated next, and 'bin' specifies the way the old vector and the trial vector are recombined. A number of other DE strategy variants also exist (Kenneth 1999; Price *et al.* 2005; Ronkkonen *et al.* 2005; Coello *et al.* 2007).

$$\text{Input}: D, G_{\max}, NP \geq 4, F \in (0,1+], CR \in [0,1], \text{ and initial bounds}: x^{(lo)}, x^{(hi)}$$

$$\text{Initialize}: \begin{cases} \forall i \leq NP \wedge \forall j \leq D: x_{j,i,0} = x_j^{(lo)} + rand_j[0,1] \cdot \left(x_j^{(hi)} - x_j^{(lo)}\right), \\ i = \{1, 2, \ldots, NP\},\ j = \{1, 2, \ldots, D\}, G = 0, rand_j[0,1] \in [0,1] \end{cases}$$

$$\begin{cases} \text{While } G < G_{\max} \\ \forall i \leq NP \begin{cases} \text{Mutation and recombine}: \\ r_1, r_2, r_3 \in \{1, 2, \ldots, NP\}, \text{randomly selected,} \\ \quad \text{except mutually different and differnt from } i \\ j_{rand} \in \{1, 2, \ldots, D\}, \text{randomly selected from each } i \\ \forall j \leq D, u_{j,i,G} = \begin{cases} x_{j,r_3,G} + F \cdot \left(x_{j,r_1,G} - x_{j,r_2,G}\right) \\ \qquad \text{if } rand_j[0,1] < CR \vee j == j_{rand} \\ x_{j,r_1,G} \end{cases} \\ \text{Select}: \\ x_{i,G+1} = \begin{cases} u_{i,G} & \text{if } f\left(u_{i,G}\right) \leq f\left(x_{i,G}\right) \\ x_{i,G} & \text{otherwise} \end{cases} \end{cases} \\ G = G + 1 \end{cases}$$

Figure 2: Basic DE algorithm (Kukkonen and Lampinen 2008)

The stagnation possibility of the DE/rand/1/bin strategy has been discussed in Lampinen and Zelinka 2000). It is possible that the search stagnates or premature convergence occurs before reaching the global optimum. These two cases can be distinguished by observing the diversity of the population (diversity is lost in the case of premature convergence). The probability of stagnation or premature convergence can be reduced by increasing the size of the population and/or F (Ali *et al.* 2012). The search can be also repeated several times to increase confidence. Adding random values from a non-finite probability (that is, Gaussian) distribution of decision variable values when the trial vector is created is sufficient to guarantee convergence to the global optimum.

3.4. Generalized Differential Evolution Algorithms

GDE requires no extra control parameters compared to the original DE, unlike several other DE approaches for constrained and/or multi-objective optimization. A primary goal of GDE has been to keep changes to DE as simple as possible and to avoid unnecessary complexity. The key idea and justification for the name is that the extension falls back to basic differential evolution in the case of an unconstrained single-objective problem. Thus, GDE is a single- and multi-objective optimizer, and relatively simple compared to the other approaches. GDE uses the DE/rand/1/bin strategy described in Section 3.2.1. This strategy was selected for GDE because of its simplicity and good observed performance. The strategy is also the most commonly used DE strategy in the literature (Coello *et al.* 2007). Different DE strategies were not compared since the main focus was the multi-objective part of the method, and not the search method used to create trial solutions. Several GDE development versions were developed and they differ in the way multi-objective optimization is performed - more precisely, how the diversity of solutions is maintained during the search. In the case of multiple objectives, all the GDE versions perform a *posteriori* optimization as other modern MOEAs.

GDE can be applied in a manner that the number of function evaluations has been reduced since the constraint-domination relation is applied at the selection stage. Even comparison between single constraint values can reveal that the trial vector does not constraint-dominate the old vector, and hence the old vector is preserved (Kukkonen and Lampinen 2008). This reduces the number of constraint function evaluations required compared to evaluation of all the constraints, an approach used with most constraint handling approaches. This reduction of constraint evaluation is helpful in the case of many and/or computationally expensive constraint functions. Different development versions of GDE are described in the following section. Their performance is demonstrated with common bi-and tri-objective test problems mentioned. Since the DE/rand/1/bin strategy has been used in the GDE versions, in theory, convergence to the Pareto-optimal front cannot be guaranteed since not all the points in the search space are necessarily attainable. However, empirically, GDE has been noted to converge well, and the latest version, GDE3, has been seen to provide good approximations of the Pareto-optimal fronts, as can be noted from the results in the following sections and related publications (Kukkonen and Lampinen 2007).

3.4.1. First Version, GDE1

GDE1, the first version of GDE was proposed by Lampinen (Lampinen 2001) as an additional improvement of the constraint handling method predicated on the dominance relation (Lampinen 2002a), and the name Generalized Differential Evolution appeared for the first time in (Kukkonen and Lampinen 2004a). For constrained multi-objective optimization, GDE1 extends the basic DE algorithm by solely modifying the selection process of DE. In GDE1, the selection operation is predicated on constraint-domination defined and can be defined as (Kukkonen and Lampinen 2008):

$$x_{i,G+1} = \begin{cases} u_{i,G} & \text{if } u_{i,G} \preceq_c x_{i,G} \\ x_{i,G} & \text{otherwise} \end{cases} \quad 3.4$$

The weak constraint-domination relation is employed to maintain congruence with the selection process of differential evolution. Hence, the trial vector is preferred in the case of equality. It should be noted that the selection is fully elitist in the sense of Pareto-dominance, i.e., the best solutions cannot be lost during the search. As mentioned earlier, one benefit of using the dominance relation in the selection is that it can be applied in such a manner that the number of function evaluations is reduced since all the objectives and constraints do not always need to be evaluated. Checking constraint violations (even for a single constraint) is often enough to decide which vector to select for the next generation (Kukkonen and Lampinen 2005b; Price *et al.* 2005). Depending on the problem, the reduction can be truly remarkable as noted (Lampinen 2002b; Kukkonen and Lampinen 2006). In practice, it is wise to evaluate computationally expensive functions last, since the last function is in the evaluation order, the fewer times it gets evaluated.

The order of the functions also has an influence on the search procedure, for the search is directed at the outset according to the first objectives and constraints. For instance, evaluation of the first constraints can determine the comparison between target and trial vectors and the rest of the constraints and objectives have no effect on the comparison. GDE1 does not possess any kind of diversity preservation, which is rare for modern MOEAs. Nevertheless, GDE1 has been able to provide good results with some problems in (Kukkonen and Lampinen 2004c). It has, however, been found to be quite sensitive to the selection of the control parameter values (Kukkonen and Lampinen 2005a).

3.4.2. Second Version, GDE2

Kukkonen and Lampinen (2004b) introduced GDE2 which is the second version of GDE, as variety preservation operation to the GDE. In GDE2, only the selection process of basic DE was modified. The process of selection is predicated on crowding of the objective space when the old and the trial vector are feasible and incomparable based on Pareto-dominance (Kukkonen and Lampinen 2008). More formally, the selection process is now:

$$x_{i,G+1} = \begin{cases} u_{i,G} & \text{if } \begin{cases} u_{i,G} \preceq_c x_{i,G} \\ \vee \\ \begin{cases} \forall j \in \{1,\ldots,K\} : g_j(u_{i,G}) \leq 0 \\ \wedge \\ x_{i,G} \not\prec u_{i,G} \\ \wedge \\ d_{u_{i,G}} \geq d_{x_{i,G}} \end{cases} \end{cases} \\ x_{i,G} & \text{otherwise} \end{cases} \qquad 3.5$$

where d_i represents distance measure which is for measuring the distance of a specific solution i to its neighbour solutions. Implementation was done using the crowding distance of NSGA-II. However, Kukkonen and Lampinen (2004b) noted that any other distance measure could be used instead of the crowding distance.

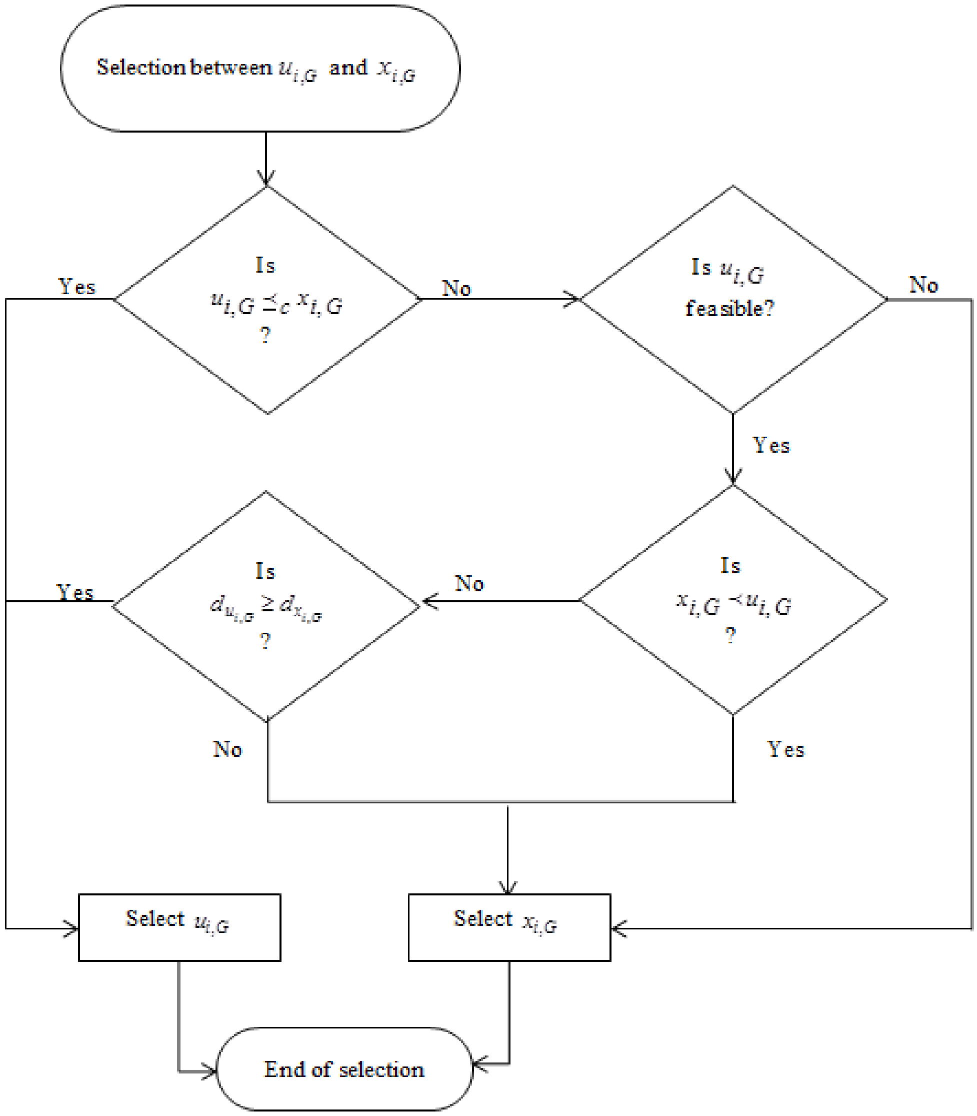

Figure 3: Operation for selection between the trial vector $u_{i,G}$ and old vector $x_{i,G}$ in GDE2 (Kukkonen and Lampinen 2004b)

The use of another distance measure is advisable if the number of objectives is more than two, since the crowding distance no longer estimates the true crowding in such cases (Kukkonen and Deb 2006). The selection operation is illustrated as a flowchart in Figure 3. Since, the Pareto-dominance relation is not the only criterion in the selection, loss of Pareto-optimal solutions is possible during the search. As non-dominated sorting is not used, crowding is measured among the whole population. The aim is to improve the extent and distribution of the attainable set of solutions. Thus, it reduces the convergence rate of the overall population as it favours obscure solutions far from the Pareto-optimal front until all the solutions are converging close to the Pareto-optimal front. The GDE2, similar to GDE1, has been noted to be quite sensitive to the selection of the control parameter values (Kukkonen and Lampinen 2008).

3.4.3. Third Version, GDE3

The third version of GDE is GDE3 (Kukkonen and Lampinen 2005b; Kukkonen and Deb 2006). In addition to the selection operation, a different part of basic DE has also been modified. At this instance, both vectors are saved when comparing feasible and incomparable solutions (the selection operation is illustrated as a flowchart in Figure 5). Hence, at the end of a generation, the population size may increase, thereby higher than the original value. Thus, based on a similar selection method as used in NSGA-II, the population is then reduced back to the original size as (Kukkonen and Lampinen 2005b) shown in Figure 4. The sorting of the population members is based on goals for a *posteriori* optimization. The worst population members according to non-dominance and crowding are removed to reduce the population size to the original size. Non-dominance is the primary sorting criterion and crowding is the secondary sorting criterion as in NSGA-II. From a non-empty set of solutions, it is always possible to find the last non-dominated set and from this set it is possible to find the most crowded solution (if two solutions have the same crowding measure, one could be selected randomly for removal). Therefore, pruning of solutions can be always performed. In order to take the constraints into consideration, non-dominated sorting is then modified. The selection process, which is predicated on the crowding distance is improved over the original technique of NSGA-II to provide a better distribution of the set of vectors (Kukkonen and Lampinen 2008).

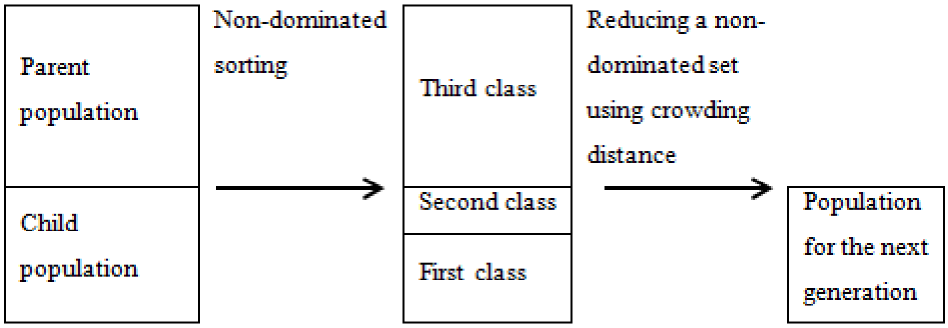

Figure 4: Selection of individuals for the next generation in NSGA-II (Kukkonen and Lampinen 2005a)

The whole GDE3 is presented in Figure 6. Parts that are new compared to previous GDE versions are framed in Figure 6. Without these parts, the algorithm is identical to GDE1. GDE3 can be seen as a combination of GDE2 and Pareto Differential Evolution Approach (PDEA). GDE3 is similar to differential evolution for multi-objective optimization (DEMO) (Ali *et al.* 2012) except that DEMO does not contain constraint handling nor recede to basic DE in the case of a single objective because DEMO modifies the basic DE (cf. Section 3.2.1) and does not consider weak dominance in the selection. Moreover, GDE3 has an improved diversity maintenance compared to DEMO. There are no constraints to be evaluated when K = 0 and M = 1, and the selection is simply

$$x_{i,G+1} = \begin{cases} u_{i,G} & \text{if } f(u_{i,G}) \leq f(x_{i,G}) \\ x_{i,G} & \text{otherwise} \end{cases} \qquad 3.3$$

This is the same as for the basic DE algorithm. The size of the population does not increase since this requires that $x_{i,G}$ and $u_{i,G}$ do not dominate each other even weakly, but in the case of a single objective, the reverse is the case. There is no need to remove elements, since the population size does not increase. Hence, GDE3 is identical to basic DE in this case.

In NSGA-II and PDEA, after a generation, the population size is *2NP*, which is then decreased to *NP*. In GDE3 and DEMO, after a generation, the population size is between *NP* and *2NP* because the population size is increased only if the trial vector and the old vector are feasible and incomparable (Kukkonen and Lampinen 2005b). This will reduce the computational cost of the whole algorithm. DEMO and GDE3 emphasize convergence over diversity more than NSGA-II and PDEA (Parsopoulos *et al.* 2004). GDE3 improves the ability to handle multi-objective optimization problems by giving a better distributed set of solutions and are less sensitive to the selection of control parameter values compared to the earlier GDE versions. GDE3 has been compared to NSGA-II and has been found to be at least comparable based on experimental results (Kukkonen and Lampinen 2008). As with GDE2 (and several MOEAs), loss of Pareto-optimal solutions is possible during the search.

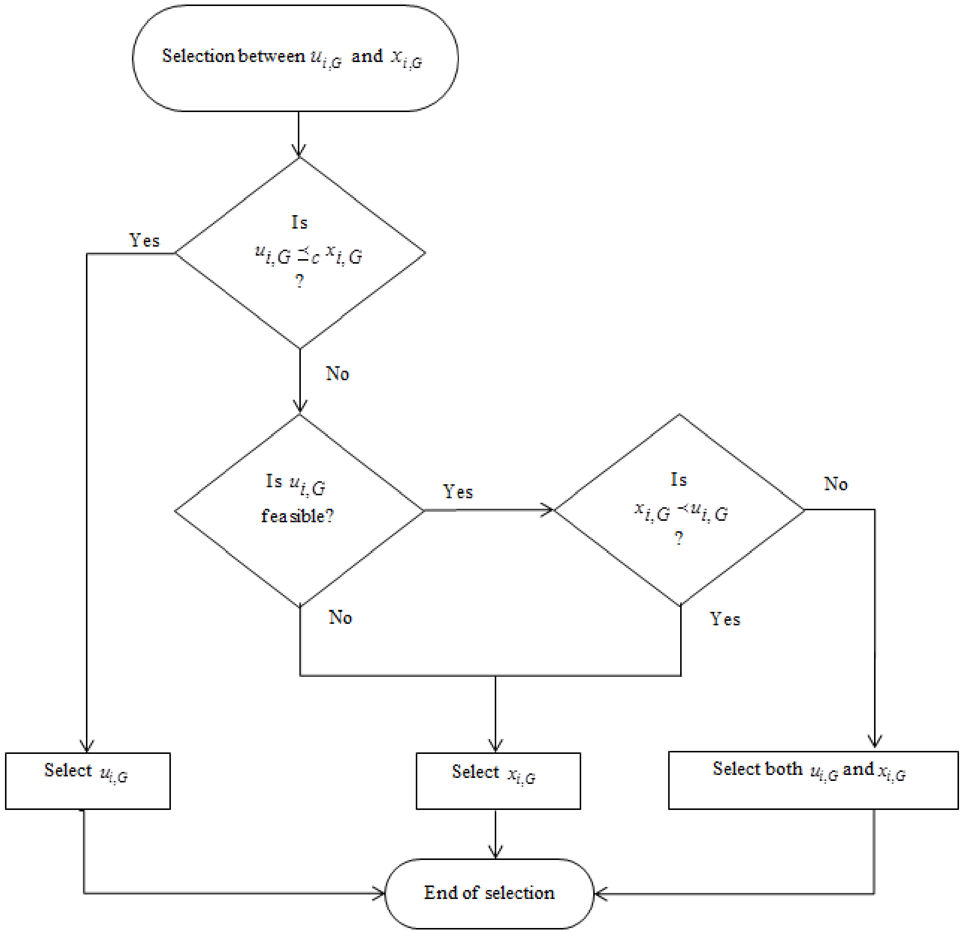

Figure 5: Operation for selection between the trial vector $u_{i,G}$ and old vector $x_{i,G}$ in GDE3 (Kukkonen and Lampinen 2005b)

$$\text{Input}: D, G_{\max}, NP \geq 4, F \in (0, 1+], CR \in [0,1], \text{ and initial bounds}: x^{(lo)}, x^{(hi)}$$

$$\text{Initialize}: \begin{cases} \forall i \leq NP \wedge \forall j \leq D : x_{j,i,0} = x_j^{(lo)} + rand_j[0,1] \cdot \left(x_j^{(hi)} - x_j^{(lo)}\right), \\ i = \{1, 2, \ldots, NP\},\ j = \{1, 2, \ldots, D\}, G = 0, rand_j[0,1] \in [0,1] \end{cases}$$

$$\begin{cases}
\text{While } G < G_{\max} \\
\forall i \leq NP \begin{cases}
\text{Mutation and recombine:} \\
r_1, r_2, r_3 \in \{1, 2, \ldots, NP\}, \text{randomly selected,} \\
\quad \text{except mutually different and different from } i \\
j_{rand} \in \{1, 2, \ldots, D\}, \text{randomly selected from each } i \\
\forall j \leq D, u_{j,i,G} = \begin{cases} x_{j,r_3,G} + F \cdot \left(x_{j,r_1,G} - x_{j,r_2,G}\right) \\ \qquad \text{if } rand_j[0,1] < CR \vee j == j_{rand} \\ x_{j,r_1,G} \end{cases} \\
\text{Select:} \\
x_{i,G+1} = \begin{cases} u_{i,G} & \text{if } f\left(u_{i,G}\right) \leq f\left(x_{i,G}\right) \\ x_{i,G} & \text{otherwise} \end{cases} \\
\text{Set}: n = n + 1 \\
x_{NP+n,G+1} = u_{i,G} \text{ if } \begin{cases} \forall j : \mathrm{g}_{\mathrm{j}}(u_{i,G}) \leq 0 \\ \wedge \\ x_{i,G+1} == x_{i,G} \\ \wedge \\ x_{i,G} \nprec u_{i,G} \end{cases}
\end{cases} \\
\begin{cases}
\text{while } n > 0 \\
\text{Select } x \in \rho = \left\{x_{1,G+1}, x_{2,G+1}, \ldots, x_{NP+n,G+1}\right\}; \\
\begin{cases} x \text{ belongs to the last non-dominated set of } \rho \\ \wedge \\ x \text{ is the most crowded in the last non-dominated set} \end{cases} \\
\text{Remove } x \text{ from } \rho \\
n = n - 1
\end{cases} \\
G = G + 1
\end{cases}$$

Figure 6: The GDE3 algorithm (Kukkonen and Lampinen 2008)

3.5. Conclusions

This chapter presented the most used DE strategy, DE/rand/1/bin with brief information on its processes. Different versions of the GDE and their properties are briefly reviewed. Each GDE version falls back to the basic DE algorithm in the case of an unconstrained single-objective problem. GDE does not contain any extra control parameter compared to basic DE. The DE/rand/1/bin strategy has been used in all the GDE versions as a search method, therefore results apply mainly to this strategy. Different strategies have different search properties that would presumably affect convergence properties when used in GDE. In GDE3, a further modification was applied to the basic DE, an example of such modification is the change in selection operation and population reduction at the end of each generation considering that the size of the population has grown during the generation.

In the case of incomparability and feasibility of solutions, both the old and the trial vectors are saved for the population of the next generation. At the end of each generation, the size of the population is reduced using non-dominated sorting and pruning based on crowding estimation. GDE3 is faster especially when solving problems having a few objectives. The time needed by the pruning technique to increase when the number of objectives and the number of non-dominated solutions to be pruned increases, but it is substantially less compared to similar approaches in MOEAs. Multi-objective optimization is fundamentally different from single-objective optimization since the population is not expected to converge to a single point. GDE3 is more robust with respect to control parameter values and provides a better diversity than other versions of GDE.

CHAPTER 4

APPLICATION AND VALIDATION OF GDE3 FOR CROP-MIX PLANNING MODEL

This chapter reports on the application of GDE3 metahueuristic evolutionary algorithm, which is introduced in chapter 3 for optimal crop-mix planning decision model. In order to apply the GDE3 metahueuristic evolutionary algorithm to practical optimal crop-mix planning decision, it is important to define and formulate the crop planning problem. It is also vital to validate the performance of the GDE3 metahueuristic evolutionary algorithm. In order to perform the validation, a performance comparison of GDE3 with that of a widely used multi-objective optimization technique was considered and the performance metrics of additive epsilon indicator, generational distance, inverted generational distance and spacing were considered for the comparative study.

4.1. Materials and Methods

A new mathematical formulation of the crop-mix planning problem is presented in this section. The model is designed to maximize the net profit and the total crop production that can be produced by minimizing the total planting area. The function's objective is to make effective use of the limited resources available in determining the hectare allocation, amongst the various competing crops that are required to be grown within the year.

4.1.1. The Crop-mix Planning Problem

There is no repudiating fact that agriculture and agricultural products play important roles in sustaining life on planet earth. Studies on agricultural farm production planning normally focus on crop alternation or rotation and crop planning. The task of crop planning is related to many measurable and non-measurable factors. These include factors such as types of land available for cultivation, yield rates of cultivated crops, weather conditions, rainfall, irrigation system, availability of agricultural inputs such as machinery, fertilizer, capital, labour cost and production cost. Along with several other factors accountable for low agricultural output are unscientific methods of cropping and natural calamities (Sarker and Ray 2009).

Suppose a country cultivates a wide variation of crops in different seasons, for instance in summer (October to February), winter (May to July) and has different land types such as single or double land type. Yield rate, cost of production and contributions are functions of soil characteristics (fertility and other soil factors), region, crop being produced, cropping pattern and method (crops being produced and their sequence, irrigation and non-irrigation). For a single-cropped land, there is a number of alternative crops from which the crop to be cultivated in a year can be selected. Similarly, there are many different combinations of crops for double-cropped (two crops in a year) and triple-cropped (three crops in a year) lands. Different combinations give different crop patterns as outputs.

The optimal crop-mix planning model is designed to maximize total net-profit. The objective is to make an optimum use of the available limited resources in order to determine the land allocation for several competing crops required to be planted in a year. The mathematical model formulation has some similarities with those in Sarker *et al*. 1997; Sarker and Quaddus 2002; Sarker and Ray 2009; Chetty and Adewumi 2014. Table 5 shows the similarities and dissimilarities of the crop planning mathematical formulation between the mentioned literatures and the current work.

Table 5: Related mathematical formulations and their dissimilarities [↑: maximization, ↓: minimization].

Author	Technique	Objective	Constraint				
			Similarities				Dissimilarities
Sarker and Quaddus (2002)	Multiple criteria decision making (MCDM) tools	↑Total contribution	Food demand	Land	Capital	Contingent	Area and import bound

Chetty and Adewumi (2014)	Current work	Sarker and Ray (2009)
Swarm Intelligence	GDE3	Multi-objective constrained algorithm (MCA)
↑Total gross profits	↑Net profit ↑Total crop production ↓Total Land	↑Total contribution ↓Working capital
	Food delivery	
Land	Land	
	Capital	
Irrigation	Labour	

Land area utilization for appropriate crops is an important issue for the crop planning decision task. The problem is to obtain net profit and annual crop production by determining the area to be used for different crops while fulfilling demand, land and capital limitations. The problem concerned in this study appears to be a well-structured optimization task and output of such a model would assist decision makers plan annual crop harvesting, which would maximize return from a given area of land. This model can be designed either as a farm level or a wide crop planning. The model was implemented for a wide crop-mix planning incorporated with data collected from South African Grain Information Service and South African Abstract of Agricultural Statistics (AAS 2012).

4.1.2. The linear crop-mix planning model

4.1.2.1. Index

The indices of the model are:

i	a crop that can be considered for production
j	a crop combination made up from i
k	the land type

4.1.2.2. Parameters

The input parameters of the model are:

P_i	price (ZAR) of crop *i* per metric ton
$V_{i,j,k}$	variable cost required of per unit area for crop *i* of crop combination *j* in land type *k*
$F_{i,j,k}$	fixed cost required of per unit area for crop *i* of crop combination *j* in land type *k*
$U_{i,j,k}$	number of farming units of crop *i* of crop combination *j* in land type *k*
$R_{i,j,k}$	planting area ratio for crop *i* of crop combination *j* in land type *k*
$G_{i,j,k}$	yield-rate that is the amount of production (metric tons) per hectare of crop *i* of crop combination *j* in land type *k*
$T_{i,j,k}$	work time for growing crop *i* of crop combination *j* in land type *k*
H_k	working time for land type *k*
W_k	land type coefficient for land type *k*
D_i	is expected delivery (metric tons) of crop *i*
L_k	available domain of land type *k*
C_a	working capital (ZAR), which indicates the total amount of money that can be invested for cropping
M	number of alternative crops for single-cropped land
N	number of crop combinations for double-cropped land
Q	number of crop combinations for triple-cropped land
M_j	a crop in each *j* for single-cropped land, $j = 1,\ldots,m$
N_j	the j^{th} crop pair of the possible crop combinations of double-cropped land, $j = 1,\ldots,n$
Q_j	the j^{th} crop triple of the possible crop combinations of triple-cropped land, $j = 1,\ldots,q$

4.1.2.3. Variables

The decision variable to the model is $X_{i,j,k}$ the area (hectare) of land to be cultivated for crop *i* of crop combination *j* in land type *k*.

4.1.2.4. First Objective function

The operating farm faces the choice of what to produce, amount to produce and method of production to employ. However, the underlying principle upon which all of these choices are based is that of profit maximization. The farm planner therefore, has to choose a production plan that is likely to maximize profit. Profit is usually defined as the numeric difference between revenue and expenditure, which can be expressed mathematically as follows:

Maximize

$$\begin{aligned} F_1 = & \sum_{j}^{m} \sum_{i \in M_j} (P_i \times U_{i,j,(k=1)} - V_{i,j,(k=1)} \times R_{i,j,(k=1)} - F_{i,j,(k=1)}) \times X_{i,j,(k=1)} + \\ & \sum_{j}^{n} \sum_{i \in N_j} (P_i \times U_{i,j,(k=2)} - V_{i,j,(k=2)} \times R_{i,j,(k=2)} - F_{i,j,(k=2)}) \times X_{i,j,(k=2)} + \\ & \sum_{j}^{q} \sum_{i \in Q_j} (P_i \times U_{i,j,(k=3)} - V_{i,j,(k=3)} \times R_{i,j,(k=3)} - F_{i,j,(k=3)}) \times X_{i,j,(k=3)} \end{aligned} \tag{1}$$

The first, second and third terms of the objective function represent net profit from single crop land, double crop land and triple crop respectively.

4.1.2.5. Second Objective function

Given the choice in terms of profit maximization and constraints that the farm faces in the production process, the farm attempts to produce a specific level of output which requires maximizing crop production. The crop production maximization is described mathematically as follows:

Maximize

$$F_2 = \sum_{j}^{m} \sum_{i \in M_j} G_{i,j,(k=1)} \times X_{i,j,(k=1)} + \sum_{j}^{n} \sum_{i \in N_j} G_{i,j,(k=2)} \times X_{i,j,(k=2)} + \sum_{j}^{q} \sum_{i \in Q_j} G_{i,j,(k=3)} \times X_{i,j,(k=3)} \tag{2}$$

4.1.2.6. Third Objective function

From the socioeconomic perspective, besides meeting food demand in the society, the attention for cultivation of profitable crops is dependent on the proper allocation of land for cultivating the crop. Crop production maximization will therefore require minimizing the planting area as follows:

Minimize

$$F_3 = \sum_{j}^{m} \sum_{i \in M_j} X_{i,j,(k=1)} + \sum_{j}^{n} \sum_{i \in N_j} X_{i,j,(k=2)} + \sum_{j}^{q} \sum_{i \in Q_j} X_{i,j,(k=3)} \qquad (3)$$

4.1.2.7. Constraints

The net profit and crop production objective functions considered are to be solved subject to five essential constraints described as follows:

***Food delivery constraint*:** This constraint represents that sum of local production and production quantity of crop *i* in a single-crop year must be greater than or equal to total requirements in the country.

$$\sum_{j}^{m} \sum_{i \in M_j} G_{i,j,(k=1)} \times X_{i,j,(k=1)} + \sum_{j}^{n} \sum_{i \in N_j} G_{i,j,(k=2)} \times X_{i,j,(k=2)} + \sum_{j}^{q} \sum_{i \in Q_j} G_{i,j,(k=3)} \times X_{i,j,(k=3)} \geq D_i \ \forall i \qquad (4)$$

Labour constraint: This constraint represents that sum of working time of crop i in a single-crop year must be less than or equal to the total working time on the farm.

$$\sum_{j}^{m} \sum_{i \in M_j} T_{i,j,k=1} \times X_{i,j,k=1} + \sum_{j}^{n} \sum_{i \in N_j} T_{i,j,k=2} \times X_{i,j,k=2} + \sum_{j}^{q} \sum_{i \in Q_j} T_{i,j,k=3} \times X_{i,j,k=3} \leq H_k \quad \forall k \ (5)$$

Land constraint: The sum of lands used for a given type of land must be less than or equal to the total available land of that type.

$$\sum_{i} \sum_{j} W_k \times X_{i,j,k} \leq L_k \quad \forall k \qquad (6)$$

Where $W_1 = 1$, for single-cropped land because no area is shared with other crops, $W_2 = 1/2$, because the same land is being used by two consecutive crops in a year on double-cropped land and W_3 = 1/3 because the same land is being used by three consecutive crops in a year on triple-cropped land.

Capital constraint: The total amount of money that can be spent for crop production must be less than or equal to the working capital or budget.

$$\sum_{j}^{m}\sum_{i\in M_j}(V_{i,j,(k=1)}\times R_{i,j,(k=1)}+F_{i,j,(k=1)})\times X_{i,j,(k=1)}+\sum_{j}^{n}\sum_{i\in N_j}(V_{i,j,(k=2)}\times R_{i,j,(k=2)}+F_{i,j,(k=2)})\times X_{i,j,(k=2)} + \sum_{j}^{q}\sum_{i\in Q_j}(V_{i,j,(k=3)}\times R_{i,j,(k=3)}+F_{i,j,(k=3)})\times X_{i,j,(k=3)} \leq C_a \qquad (7)$$

Non-negativity constraint: The decision variables must be greater than or equal to zero.

$$X_{i,j,k} \geq 0 \ \forall \ i, j, k \qquad (8)$$

4.1.3. Solving the crop-mix planning model

There are more than 207 different crops cultivated in South Africa. A full-scale model, considering all these crops, would consist of more than 789 constraints and 550 variables. This is a big problem, but decision makers are interested only in major crops and aggregate information on other crops. Thus, all the crops are divided into 8 major groups, such as deciduous fruit and viticulture, field crops, vegetables, citrus fruit, subtropical fruits, flowers, nuts and other horticultural products. Fruits, bananas and some other whole-year crops are grouped together accordingly. Herbs, rooibos tea and some seeds and seedlings are also whole-year crops and they are grouped as other horticultural products. The number of crop combinations identified for single, double and triple-cropped lands is m = 8, n = 14 and q =3, respectively, according to the present cropping pattern. Any of the 8 major groups of crops can be produced in a year in the single-cropped land. There are 14 pairs of crops that can be produced (one after another of the pair) in a year in double-cropped lands while 3 combinations (three crops in each group, one after another in a year) in triple-cropped lands. In fact, the 14 pairs and the three triples of crops consist of the 8 crops were grouped.

4.2. Comparison of Multi-Objective Optimization Algorithms

The multi-objective optimization techniques studied are briefly discussed to put the work in a clear perspective. In this section, non-dominated sorting genetic algorithm (NSGA-II), which is one of the most popular evolutionary techniques and Generalize Differential Evolution 3 (GDE3) algorithm are explored to solve a variant of optimal crop planning decision problem formulated.

4.2.1. Generalized Differential Evolution (GDE3)

The GDE3 is the third version of the GDE that modifies the selection rule of the basic differential evolution, extends DE/rand/1/bin strategy as presented in Section 3.2.1, to problems with *M* decision objectives and *K* constraint functions. The reader should refer to Section 3.3 for additional details

4.2.2. Non-Dominated Sorted Genetic Algorithm II (NSGA-II)

The NSGAII is a second generation MOEA developed by Deb *et al.* (2002) which made significant improvements to the original NSGA by (i) using a more efficient non-domination sorting scheme, (ii) eliminating the sharing parameter, and (iii) adding an implicitly elitist selection method that greatly aids in capturing Pareto surfaces (Wang *et al.* 2011). In addition, the NSGA-II can handle both real and binary representations. The NSGA-II was chosen for comparison in this study because it has been successfully employed in prior crop planning studies (Sarker and Ray 2009). For the crop planning problem, all of the algorithms evaluate potential solutions in terms of a vector of objectives.

The concept of Pareto-dominance is used to assign fitness values to the sampling solutions. For example, a solution x_1 dominates another solution x_2 if and only if it performs as well as x_2 in all objectives and better in at least one objective. The fast non-domination sorting approach of the NSGA-II ranks each solution according to the number of solutions that dominate it. Once fitness is assigned, two-step crowded binary tournament selection is performed. In cases where two solutions have different ranks, the individual with the lower rank is preferred. Alternatively, if both solutions possess the same rank, then the solution with the larger crowding distance is preferred. Solutions with higher crowding distances add more diversity to the solution population, which helps to ensure that the NSGA-II finds solutions along the full extent of the Pareto surface.

4.3. Experimental Design

In this section, the researcher present the experiments conducted and discuss the results obtained. To allow a fair comparison among the approaches used, a criterion normally used in evolutionary multi-objective optimization was adopted; all the algorithms were performed for the same number of fitness function evaluations and the combination of parameters chosen for each of the algorithms compared was appropriate for the approach to have a reasonably good performance. This can be corroborated by checking the original sources of each of the methods compared. The NSGA-II and GDE3 methods were implemented using NETBEAN version 7.3, on an HP PC with Pentium dual core processor having 2.30GHz clock speed and 4GB of RAM.

4.3.1. Parameter Setting

In this section, the NSGA-II and the GDE3 were parameterized according to the most commonly recommended settings from the evolutionary multi-objective optimization literature. The relevant parameterization of each of the algorithms is summarized in Table 6.

Table 6: General Setting for the Parameters

	NSGA-II	GDE3
Population size, N	100	100
Termination criteria	200,000 Evaluations	200,000 Evaluations
Crossover Probability, p_c	0.9	-
Crossover dist. Index, p_m	20	-
Crossover Rate, CR	-	0.9
Scaling Factor, F	-	0.5

Mutation Probability, η_c	$1/N$	-
Mutation dist. Index, η_m	20	-
Variable representation	Real	Real

In order to accurately assess the reliability of each algorithm, 50 random seeds were chosen resulting in 50 random seed trial runs for each algorithm. The reader should note that identical random seeds were specified for the NSGA-II and the GDE3 since they all use the same random number generator. The impacts of random number generator differences were minimized by using 50 trial runs for statistical performance assessment of each multi-objective evolutionary algorithm. In order to facilitate a fair performance comparison, the average number of design evaluations that it required to automatically terminate was used as a basis for parameterizing the runtime of the NSGA-II and the GDE3, for the same random seeds. Parameterizing the runtime of the algorithms in this manner gave each algorithm the same opportunity to generate the Pareto front of the crop planning problem.

4.4. Results and Discussion

4.4.1. Performance Metrics

Four performance metrics are used: additive epsilon indicators, generational distance, inverted generational distance and spacing (Zitzler *et al.* 2003) are used to evaluate the average final performances of the algorithms. The performance metrics used in this study require a reference solution set for comparison purposes. The reference set can represent the true Pareto-optimal solution set or the best known approximation to the Pareto-optimal set attained through previous algorithm runs or by other means. In this study, if a metric required a reference set, the true Pareto-optimal set for the crop planning problem was used.

The additive epsilon indicator proposed by Zitzler *et al.* (2003) make direct use of Pareto dominance and is highly intuitive. For two approximation sets *A* and B, epsilon indicator can be thought of as a measure of minimum distance to shift set *B* so that set *A* only just dominates it. A set of objective vector is called approximation set if any element of the set does not weakly dominate any other objective vector in set (Zitzler *et al.* 2003).

The generational distance measures the average distance of solutions to the Pareto-optimal front. Thus, from each solution, the shortest distance to the Pareto optimal front is measured and then the mean of these distances is calculated (Zitzler *et al.* 2003). Inverted generational distance measures the average distance of the Pareto-optimal front to the solutions. Thus, from each member of the Pareto-optimal front (approximation), the shortest distance to the set of solutions is measured and then the mean of these distances is calculated (Zitzler *et al.* 2003). It indicates how far is the true Pareto-optimal front from the front obtained by each of the algorithm. An algorithm A is better than algorithm B in terms of convergence, if the inverted generational distance of algorithm A is less than the inverted generational distance of an algorithm B. Spacing measures the standard deviation of the distances from each solution to the nearest solution in the obtained non-dominated set (Knowles and Corne 2002).

4.4.2. Performance Results

The constrained multi-objective crop planning model was solved using GDE3. Four different types of optimization problems solved in this model. The results obtained using GDE3 is compared with the results of NSGA-II. The first optimization is formulated with three objectives of maximizing both total net profit, total crop production and minimizing total planting area. Figures 7 and 8 show the Pareto optimal front produced for the crop-mix planning model when maximizing total net benefit, total crop production and minimizing total planting area.

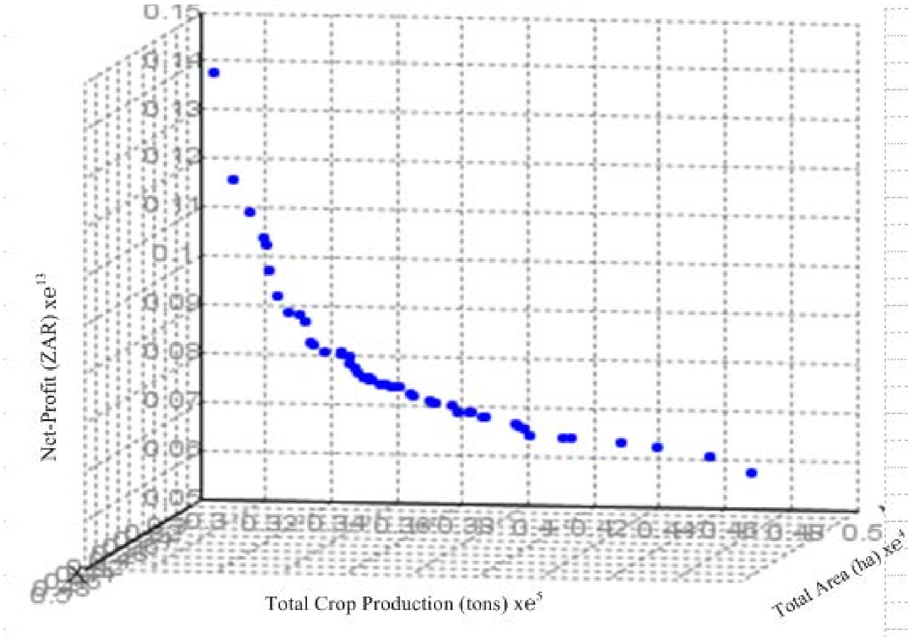

Figure 7: Pareto optimal front produced by GDE3 for the crop-mix planning model when maximizing total net profit, total crop production and minimizing total planting area.

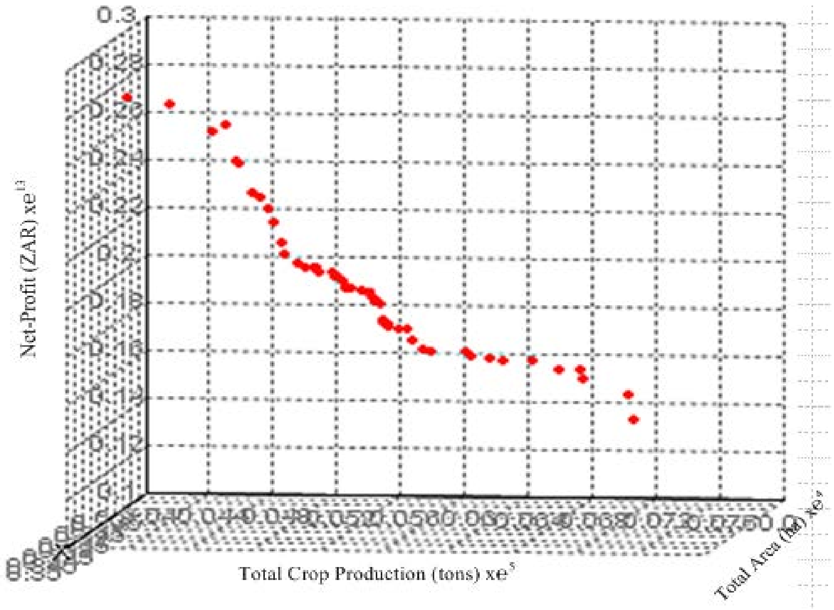

Figure 8: Pareto optimal front produced by NSGA-II for the crop-mix planning model when maximizing total net profit, total crop production and minimizing total planting area.

The results of the second optimization problem are presented in Figures 9 and Figures 10. The second optimization has two objectives of maximizing total net-profit, and total crop production. Figure 9 and Figure 10 presents the Pareto optimal front produced for the crop-mix planning model when maximizing total net-profit and total crop production.

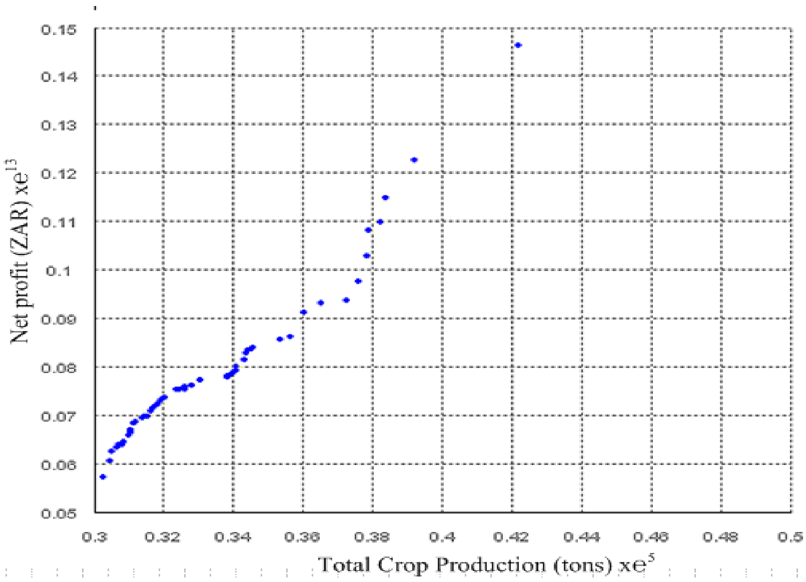

Figure 9: Pareto optimal front produced by GDE3 for the crop-mix planning model when maximizing total net-profit and maximizing total crop production.

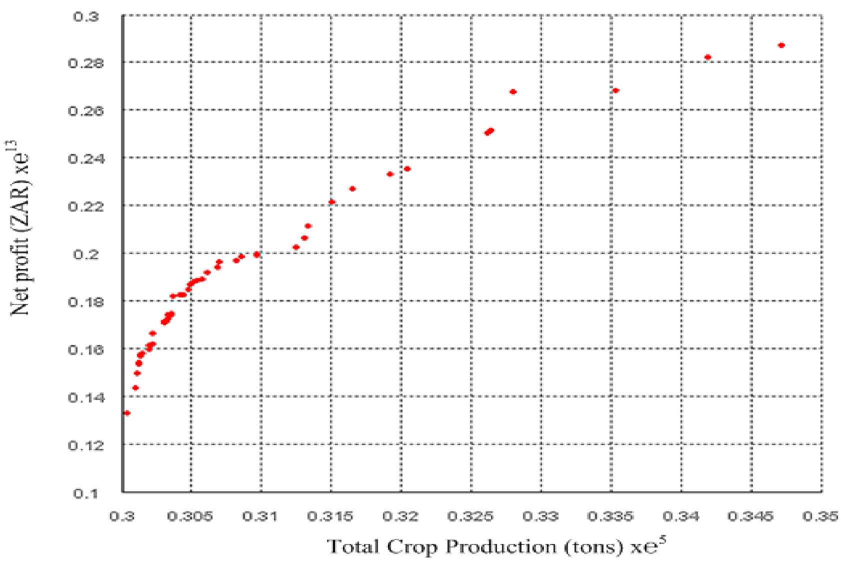

Figure 10: Pareto optimal front produced by NSGA-II for the crop-mix planning model when maximizing total net-profit and maximizing total crop production.

Figures 11 and 12 present the results for the third optimization problem for two objectives of maximizing total net-profit and minimizing total planting area. Figures 11 and 12 presents the Pareto optimal front produced for the third optimization problem.

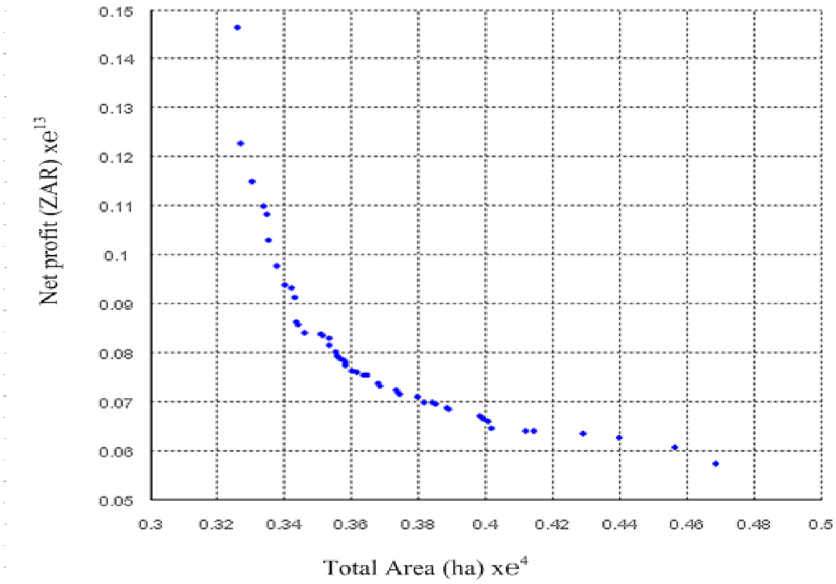

Figure 11: Pareto optimal front produced by GDE3 for the crop-mix planning model when maximizing the total net benefit and minimizing total planting area.

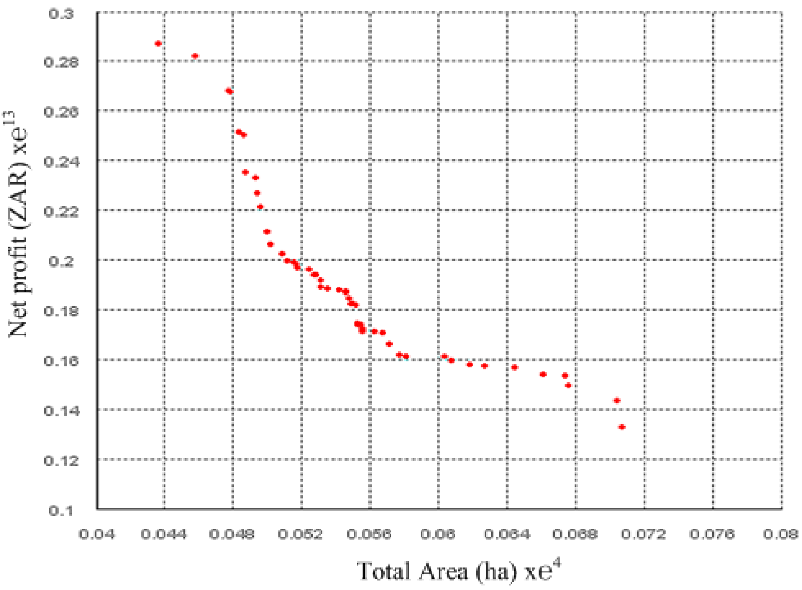

Figure 12: Pareto optimal front produced by NSGA-II for the crop-mix planning model when maximizing the total net benefit and minimizing total planting area.

The last optimization also has two objectives of maximizing total crop production and minimizing total planting area. The results are presented in Figures 13 and 14. Figures 13 and 14 present the Pareto optimal front produced for the crop-mix planning model when maximizing total crop production and minimizing total planting area.

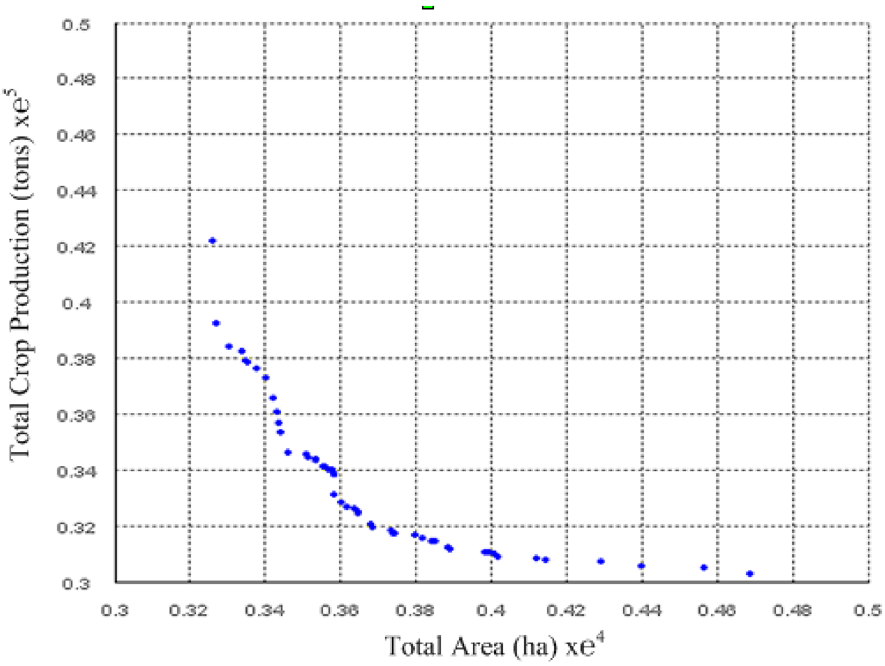

Figure 13: Pareto optimal front produced by GDE3 for the crop-mix planning model when maximizing total crop production and minimizing total planting area.

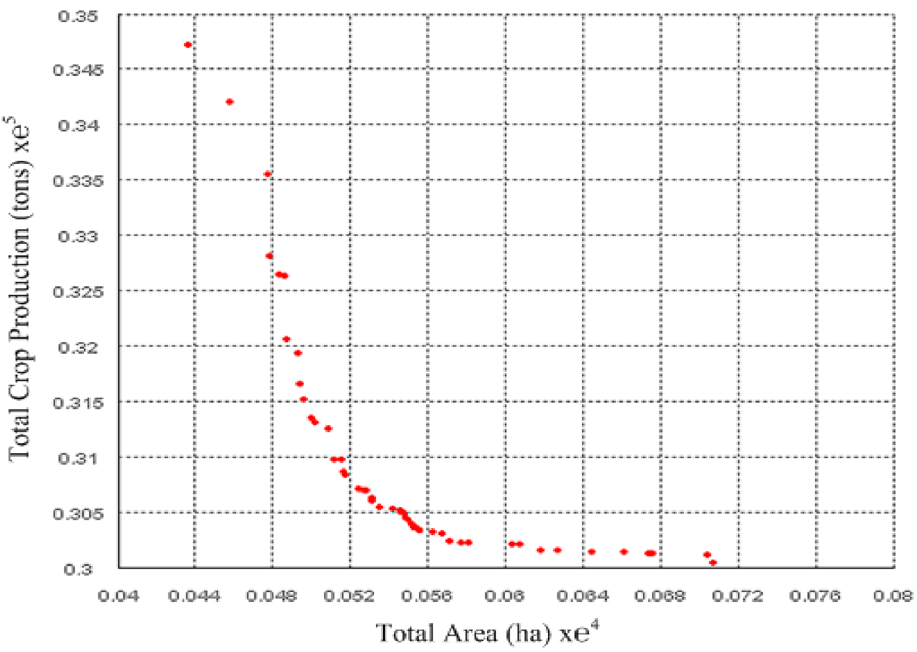

Figure 14: Pareto optimal front produced by NSGA-II for the crop-mix planning model when maximizing total crop production and minimizing total planting area.

In figure 7 – 14, the solutions converge to Pareto front. The solutions are also diverse on the Pareto front. All the solutions on the Pareto optimal front are equally good. In the model, all the three objectives can be satisfied at the same time. An improvement in one objective will prompt a change in the other objectives. In the Pareto front, a solution is not better than the others in all the objectives. In practice, a decision-maker ultimately has to select one solution from this set for system implementation (Adeyemo and Otieno 2010a). In a multi-objective optimization, there cannot be a solution that will satisfy all the objectives but instead, there are sets of solutions in one simulation run which correspond to non-dominated solutions (Deb 2001). It depends on a farmer to choose the best solution that suits him from the set of non-dominated solutions. The solutions are optimal in the sense that no other solution in the search space is superior to them when all the objectives are considered.

The goal of multi-objective problem is to find as many Pareto-optimal solutions as possible to reveal trade-off information among different objectives (Deb

2001). Once such solutions are obtained, higher level decision maker will be able to choose a final solution with further considerations like water availability, number of workers, equipment availability, the capital available, land area, market situation and available storage facilities (Adeyemo and Otieno 2010b) as also the case in this study. Coefficient of determination R^2 was computed for each of the Pareto front obtained from the algorithms. It measures the global fit of the Pareto front. R^2 is an element of [0, 1] and represents the proportion of variability in y that may be attributed to some linear combination of the regressors in x. Table 7 shows the regression statistics for the four different types of optimization problems solved in this model. It reveals that GDE3 produced a higher coefficient of determination compared to NSGA-II.

Table 7: Regression Statistics

	Optimization 1		Optimization 2		Optimization 3		Optimization 4	
	GDE3	NSGA-II	GDE3	NSGA-II	GDE3	NSGA-II	GDE3	NSGA-II
R^2	0.9995	0.9993	0.9735	0.9711	0.9998	0.9994	0.9749	0.9710
Adj. R^2	0.9995	0.9992	0.9729	0.9705	0.9997	0.9994	0.9744	0.97039

Table 8 shows the results of the average additive epsilon indicator. The average additive epsilon indicator results reveal that the additive epsilon indicator measure achieved by the GDE3 is an order of magnitude lower than that achieved by the other algorithm indicating superior performance. In addition, the GDE3 achieves the lowest standard deviation of all algorithms in this measure. The worst overall performer, in terms of average value and standard deviation was NSGA-II

Table 8: Additive Epsilon Indicator Metric (10^{-3})

	Best	*Average*	*Worst*	*Std. Dev.*
GDE3	7.59	8.24	9.65	0.431
NSGA-II	8.29	9.16	10.5	0.726

The generational distance metric represents the smallest distance on average that an algorithm's approximation sets must be translated to completely dominate the true Pareto-optimal set. Table 9 shows the results of generational distance metric, the results indicate that the GDE3 requires the smallest average translation distance and that the NSGA-II requires the largest translation distance on average. In addition, the GDE3 achieves the smallest standard deviation in this measure compared to the other algorithm.

Table 9: Generational Distance Metric (10^{-3})

	Best	*Average*	*Worst*	*Std. Dev.*
GDE3	2.15	3.45	6.87	1.48
NSGA-II	2.73	4.06	7.10	1.74

Table 10 shows the results of inverted generational distance. The results of inverted generational distance metric indicate that the GDE3 produced the shortest distance between the true Pareto front and the NSGA-II produced the longest distance between the true Pareto front. In addition, the GDE3 achieves the smallest standard deviation in this measure compared to the other algorithm.

Table 10: Inverted Generational Distance Metric (10^{-3})

	Best	*Average*	*Worst*	*Std. Dev.*
GDE3	2.40	2.81	3.15	0.171
NSGA-II	2.62	3.52	4.39	0.398

Table 11 shows the results of spacing. Evaluation of the spacing indicator is based on the standard deviation of the solutions. From table 10, it can be seen that GDE3 found the best results with very average values 0.001469 compared to NSGA-II with a value of 0.001534.

Table 11: Spacing Metric (10^{-3})

	Best	*Average*	*Worst*	*Std. Dev.*
GDE3	1.070	1.469	1.69	0.415
NSGA-II	1.231	1.534	2.038	0.653

4.5. Conclusions

This work suggests that Generalized Differential Evolution 3 (GDE3) is a useful multi-objective optimization tool for optimal crop planning decision making. It has been shown that GDE3 can be successfully employed to search the feasible solution space for a complex crop-mix planning problem that involves multiple objectives and multiple constraints. The GDE3 algorithm also uses a very simple mechanism to deal with constrained functions and results generated by the algorithm indicate that such mechanism, despite its simplicity, is effective in practice.

From this study, it can be concluded that GDE3 is practically effective for optimal crop planning decision making. Given the features of GDE3, an extension of the paradigm for multi-objective optimization can be particularly useful to deal with dynamic functions. As part of future work, other optimization methods can be compared to GDE3 to establish its superiority over many other methods for crop planning decision making. The performance comparison of these optimization algorithms is valuable for a decision maker to consider tradeoffs in method accuracy versus method complexity. Finally, future work will extend GDE3 for crop planning decision under uncertainty. This will produce a novel approach to deal with practical situations for which profit coefficients of agriculture are uncertain. In the future, the researcher plans to deploy the implementation of this approach as mobile web services to make the approach more useful to anyone desiring to engage in subsistence farming.

CHAPTER 5

DEVELOPMENT OF AN OPTIMAL CROP PLANNING SYSTEM

This chapter presents the development of an optimal crop planning system to support farmers in strategic crop planning decision making. The purpose of the system is to legitimize the idea behind the modeling of optimal crop-mix planning problems. Section 5.2 presents the implementation of the decision support system including its various components. Section 5.3 discusses how the crop planning decision support system works. The proposed system is a web-based application that is accessible through mobile devices such as smart phone and tablet devices with an internet connection.

5.1. Modelling Optimal Crop Planning System

The GDE3 algorithm for crop mix planning model (cf. section 3.4.3) as shown in Figure 6 has to be designed into a tool at this stage to assist and support the decision process. In realizing a system design, it is important to first present the system models. In doing this, the use case scenarios, and functional requirements have to be modelled using the Use Case Narration (UCN). The researcher has decided to apply UCN because it is a textual representation of the course of events encountered when an actor is interacting with the system (Popel 2003). Use case diagrams just give an overview of the possible scenarios in the system and their relationships. Narrations are the place where the business concentrates and the explanation of what happens in each scenario is provided. Use case narrations help identify possible misunderstanding during the very early stage of software implementation. The use case narrative describes each use case in detail as a path traversed through the system to meet a requirement; it often helps to visualize the system in action and is a meeting place of what the client want to get and what the developers think to build (Popel 2003). A use case narration in formal style includes not only a typical success story of using the system, but also to explicitly document several other points which help modern software processes to compare several implementation options to come up with better usable system even in a time boxed environment (Popel 2003; Bruegge and Dutoit 2004; Martin 2004).

The decision support system was modelled using UCN to provide clear and concise representation of the processes and related components that would be triggered by related tasks. Table 12 presents the use case narration summary of the decision support system.

Table 12: Summary of the Decision Support System Use Case Narration

USER CASE ID:	**USER CASE NAME:**
USC-1.	Register User.
USC-2.	Login user.
USC-3.	View Crop Combination Group.
USC-4.	View Possible Crop Combinations.
USC-5.	Perform Optimization.
USC-6.	Add crop data
USC-7.	Update crop data.

The UCN involves Actor (Primary business actor and other participating actor), interested stakeholders, use case description, preconditions, triggers, typical course of events, alternate courses, conclusions, post-conditions, business rules, implementation constraints and specification, assumptions and assertions. The primary business actor is the stakeholder who primarily benefits from the execution of the use case by receiving something of measurable or observable value. Other participating actors include system actors, server/receiver actors, facilitating actors and secondary actors. Interested stakeholders are those who are concerned about the use case. Precondition describes what should be true before this scenario can occur. Preconditions are assumed to be true in the use case narrative. Triggers are the events that initiated the scenario. Typical course of events are the main steps to the goal and alternate courses are an extension to the main steps. Conclusion specifies when the use case successfully ends. Post-condition describes what should be true on successful ending of the use case. Business rules are the policies and procedures of the business that the system should conform to in order for the system to be useful. A detailed information on the decision support system use case narration is presented in the appendix.

Figure 15 presents the graphical user interface layout diagram, which shows web pages in the application and how they are interrelated. The system documentation entails the implementation converting system requirements into a system specification and coding the specification to realize the decision support system. This activity involved translating the modelled UML diagrams and developing the system in an operational environment (Shelly *et al.* 2010).

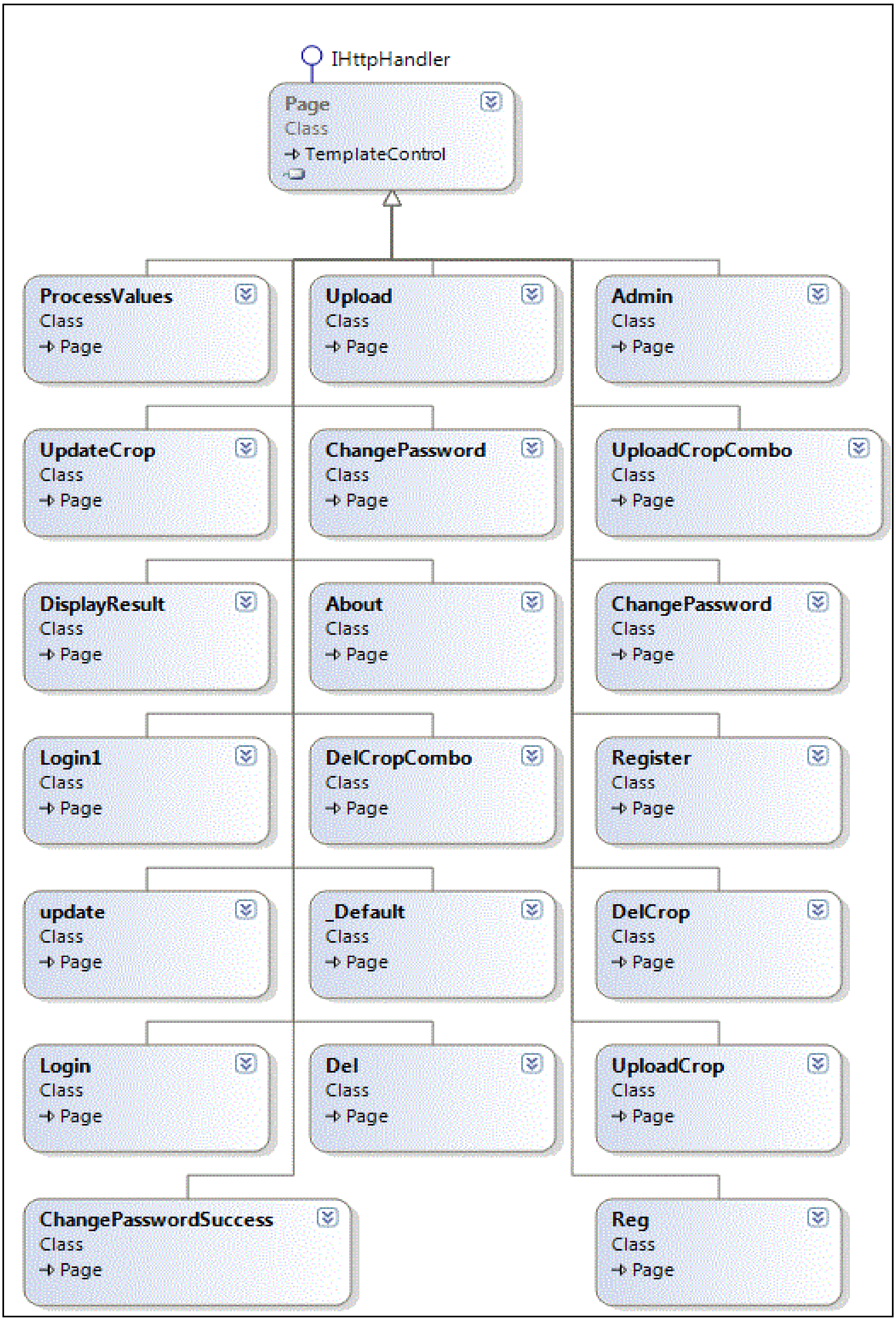

Figure 15: Graphical User Interface (GUI) Layout Diagram

For this study, the object was implemented in a form of a functional system. However, the system development and implementation also include the developmental stages such as the construction of models and methods of solving a problem in a new context (Hevner *et al.* 2004). From the models, higher level components such as the databases and user interfaces were developed. The alternative operating technology platforms were also implemented, including technical elements such as the data structure and programming language. A class diagram is a graphic presentation of the static view that shows a collection of declarative (static) model elements, such as Classes, Interfaces, Types and their contents and relationships (Thomas 2012). A class diagram may show a view of a package and may contain symbols for nested packages. A class diagram contains a certain reified behavioral elements, such as operations, but their dynamics are expressed in other diagrams, such as state-chart diagrams and collaboration diagrams (Thomas 2012). In class diagram, the classes represent both the main objects, interactions with the application and the classes to be programmed. Class diagrams capture the static structure of Object-Oriented systems, or how they are structured rather than how they behave. Class diagrams represent the basic principle of object oriented systems because they identify system components as entities and depicts the interrelationship between the entities.

Figure 16 and 17 present the database class diagram and the GDE3 class diagram respectively. The database class diagram is used to present the entity-relationship model in the system design. The entity-relationship model adopts the more natural view that the real world consists of entities and relationships. It incorporates some of the important semantic information about the real world. Database entity class diagram is used for visualizing conceptual data structure and physical database schema. This application supports conceptual, logical and physical data modelling. Specifically, the GDE3 class diagram is used to show the static structure diagram of classes and their possible relationships, such as association, inheritance, aggregation and dependency. It describes the structure of the GDE3 classes their operations, attributes, and the relationships among the classes.

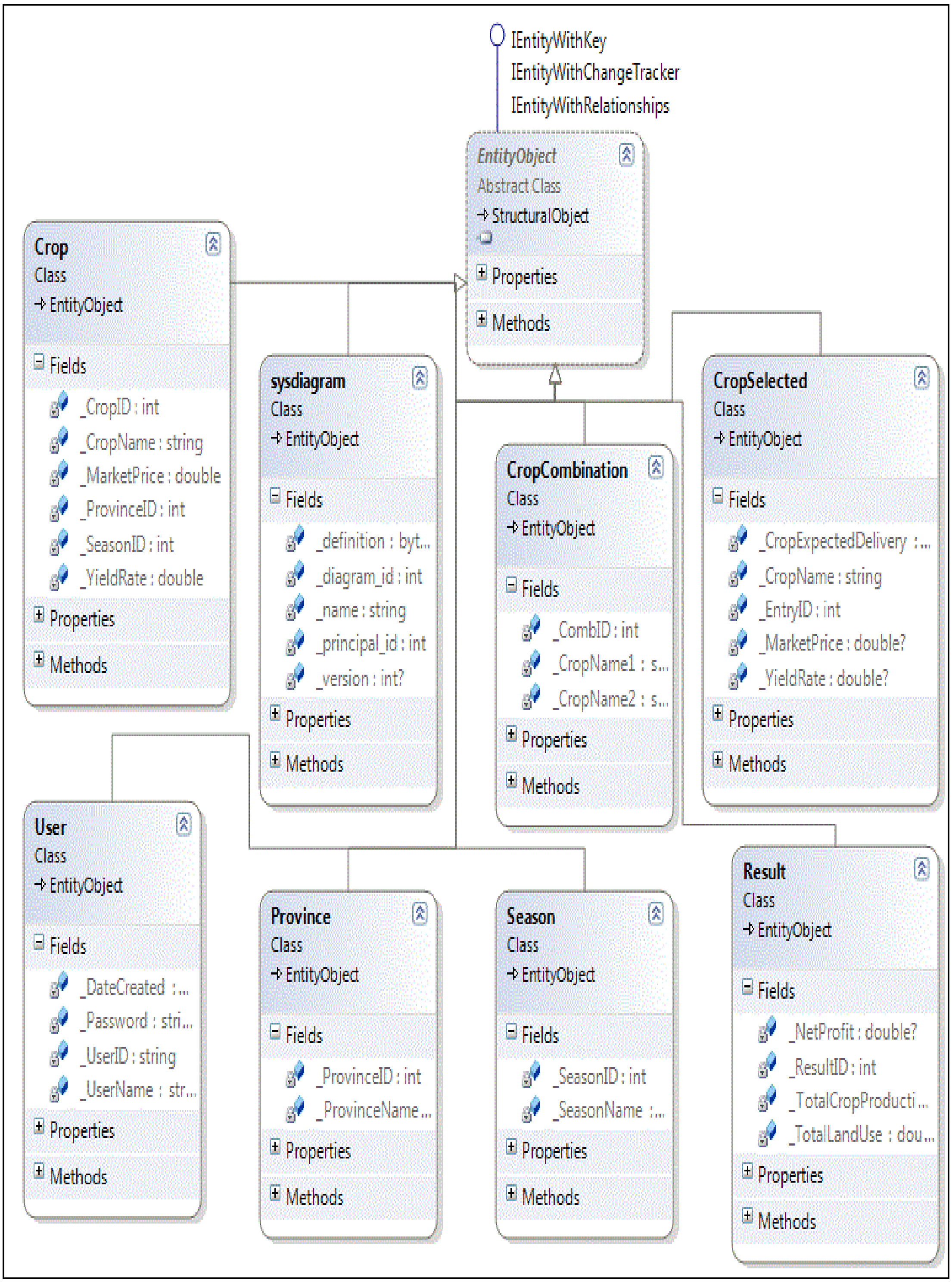

Figure 16: Database Class Diagram

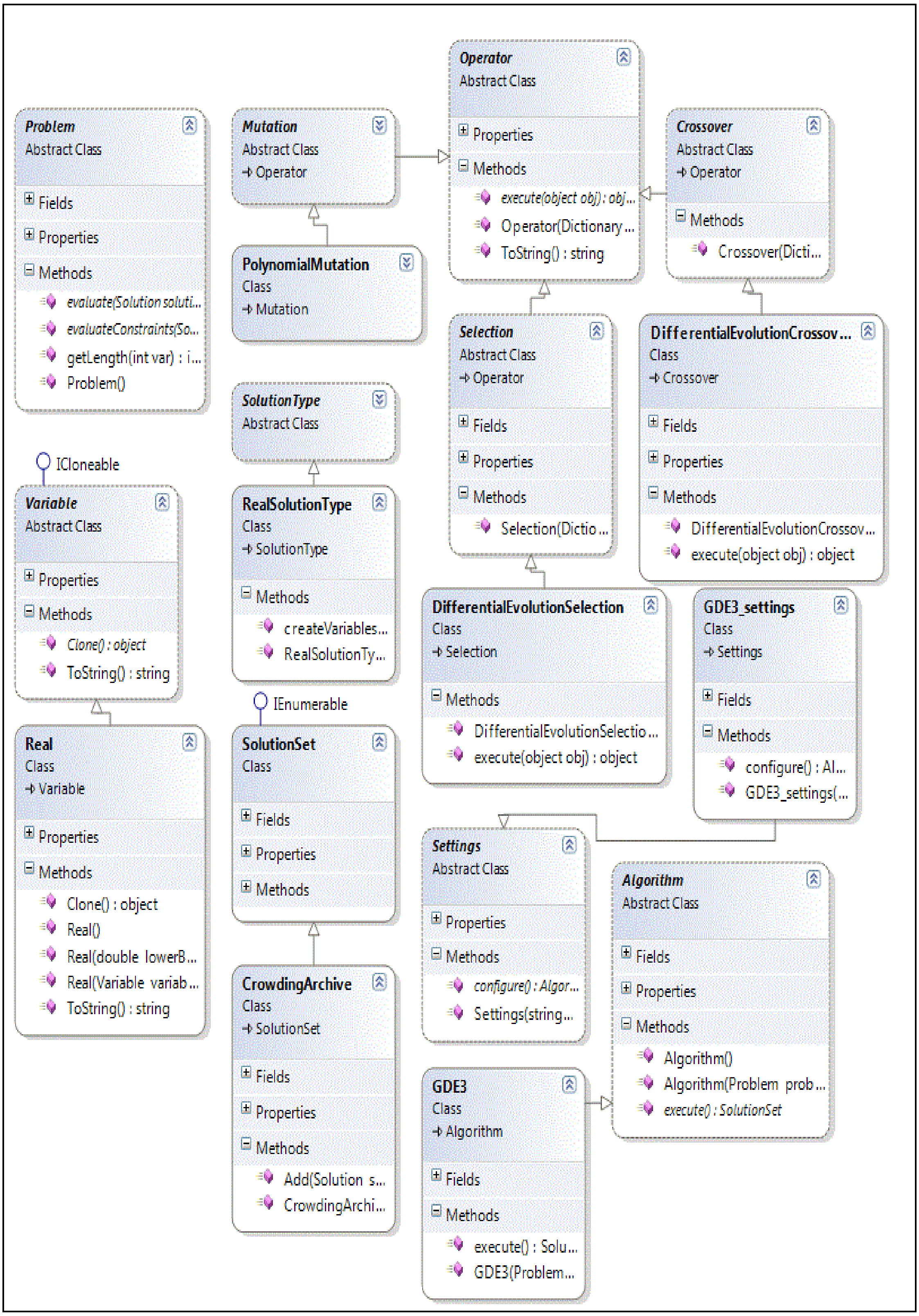

Figure 17: The GDE3 Class Diagram

5.1.1. System performance and evaluation

The evaluation phase allows testing the efficacy of the system (Hevner *et al.* 2004) in addressing the problem in the context it was established (Ellis and Levy 2010; Levy and Ellis 2011). The evaluation phase presents the evaluation criteria and limitation of the evaluation of the decision support system. The evaluation results serve to validate the relevance and merit of decision support system for strategic decision making in crop planning. The performance evaluation of GDE3 was compared with another state-of-art evolutionary algorithm for the crop planning problem which was presented in Chapter 4.

5.2. Implementation of Optimal Crop Planning System

This section presents the implementation of the decision support system called CPLANNER to provide proof-of-concept through a real life model implementation. The implementation demonstrates relevance in the farm management domain. The prime objective of the research was to develop a decision support tool for assisting local farmers to make optimal strategic decisions in crop farming system. The proposed system should therefore assist local farmer to make the optimal strategic decision in crop planning. The varied operation provided by the system could be used for crop planning related operations such as land allocation, and crop selection to allow informed decision making. The prototype system provides basic related functions such as capturing crop information, managing the information on crop combination. The data recorded are stored in the database for easily accessible for future retrieval, analysis and use in various planning and decision making processes. The prototype system is relatively easy to use and simple to accommodate basic users with very little literacy levels to skilled users.

5.2.1. Functional description of crop planner (CPLANNER)

The CPLANNER application requires for the local farmer to register with a user name and password for authentication purposes. User authentication is required for the farmer to log in and use the application as shown in Figure 18. The application will then authenticate the user and load the main interface of the application to allow the user to use the system for his/her crop planning problem. Overall, the system allows the user to complete as many processes as possible without delays and deviation from the processes.

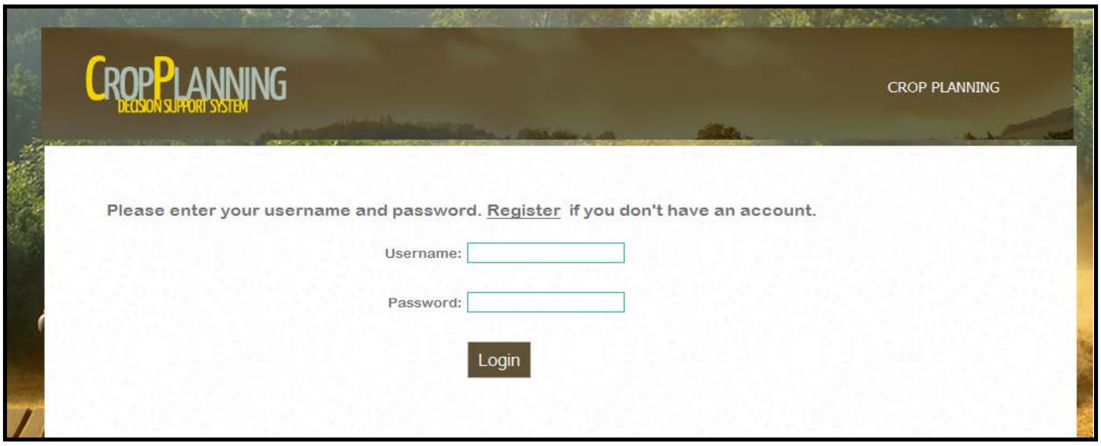

Figure 18: User authentication

Once the user is authenticated, the main operation page of the application is displayed in user interface to access as shown in Figure 19.

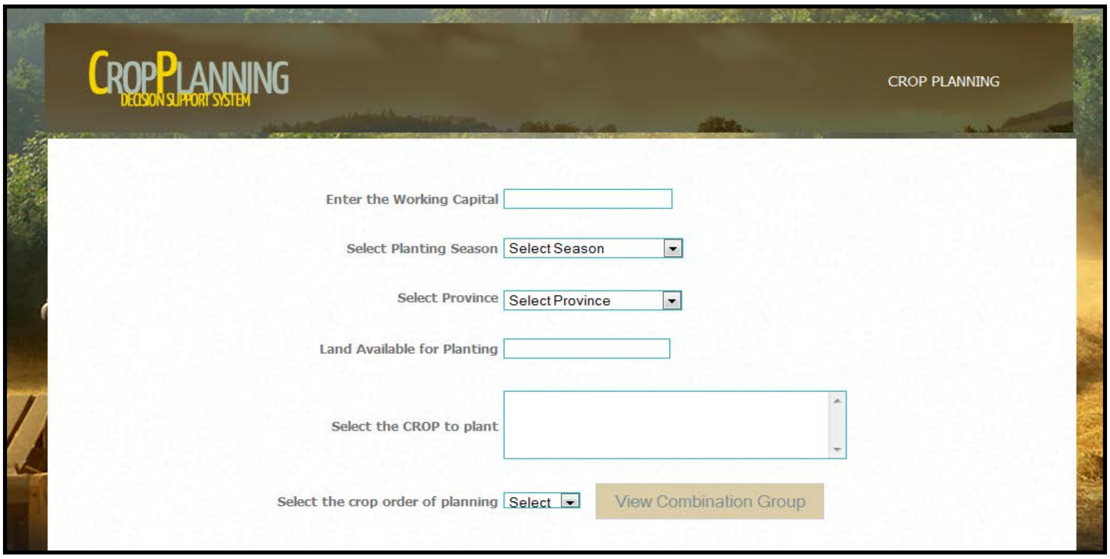

Figure 19: The main operation page on the CPLANNER

The main user interface provides simple and easy accessibility of the application's main functionality. This enables users to complete their task in a quick and concise manner without navigation through too many controls on the user interface.

5.2.1.1. Adding crop/ crop combination information

The crop details and crop combination information are recorded through Add Crop/Crop Combinations functionality as shown in Figure 20 and stored in the crops and crop combinations table respectively for easy accessibility. The Add crop/crop combinations functionality is used by the administrator; it helps the administrator to insert new crop and crop combinations.

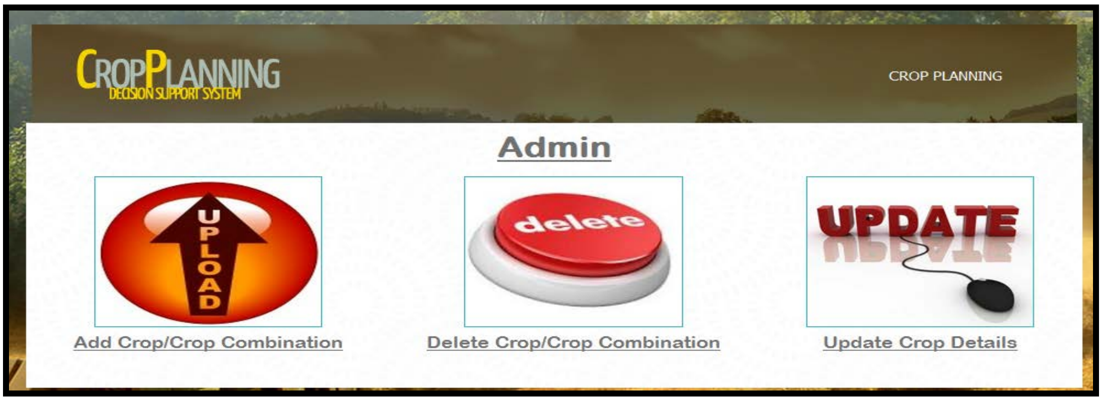

Figure 20: Administrator Home page

Once the administrator clicks on the functionality, it connects the administrator to a page where the administrator can perform the operation separately as shown in Figure 21.

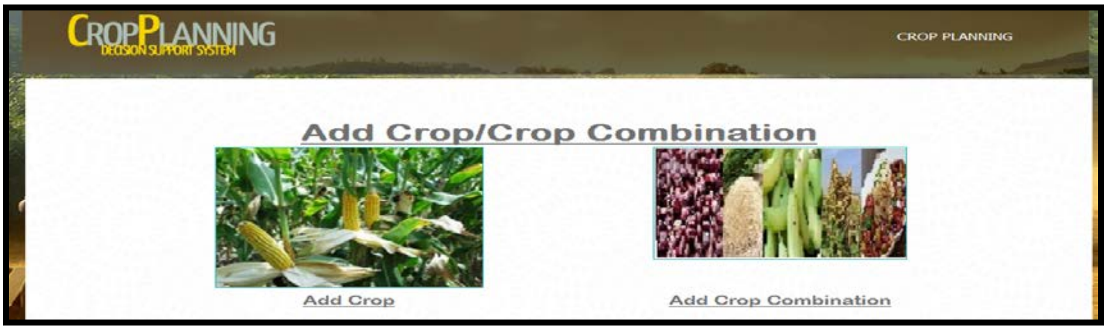

Figure 21: Add Crop/Crop Combination page

If the administrator clicks on the Add crop function, Figure 22 is displayed but if the administrator clicks on the Add crop combination function, Figure 23 is displayed.

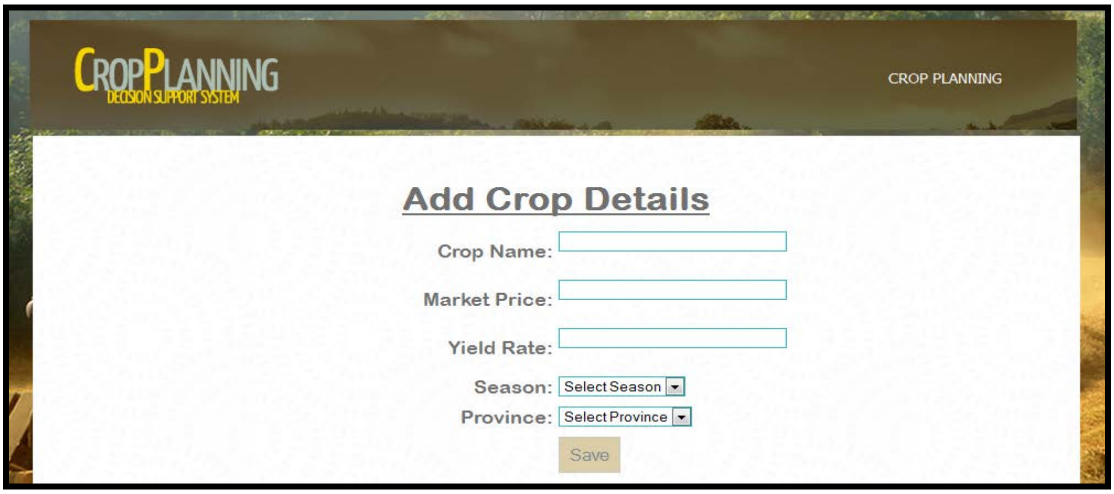

Figure 22: Add crop details page

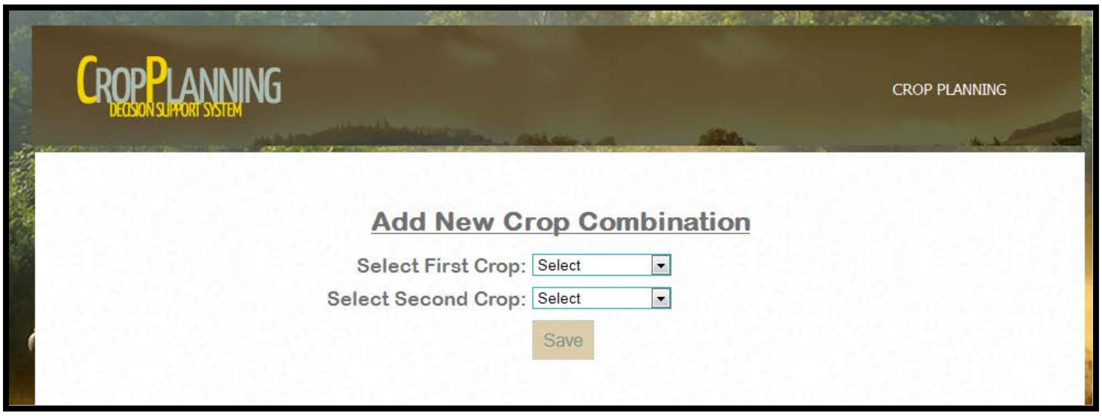

Figure 23: Add crop combination page

5.2.1.2. Editing crop information

The crop details information are edited through update crop details functionality as shown in Figure 20. The update crop details functionality is used by the administrator to update crop details. Based on the dynamic nature of some of the crop information such as yield rate and market price, there is a need to update such information on a regular basis. Once the administrator click on the update crop details function; Figure 24 appears on the interface.

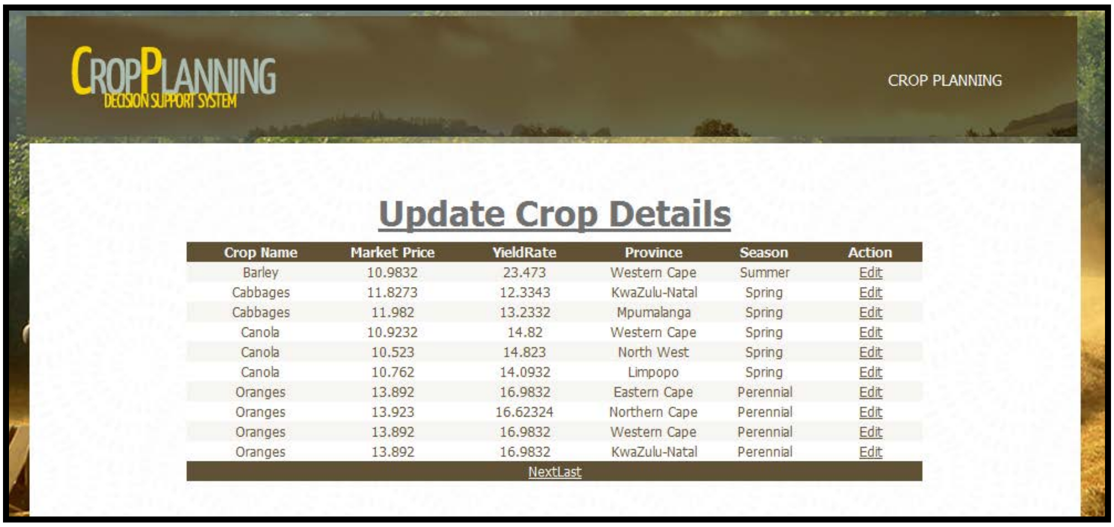

Figure 24: Update crop details page

To update the crop information, the administrator clicks on the “edit” button and update the specific crop information as shown in Figure 25.

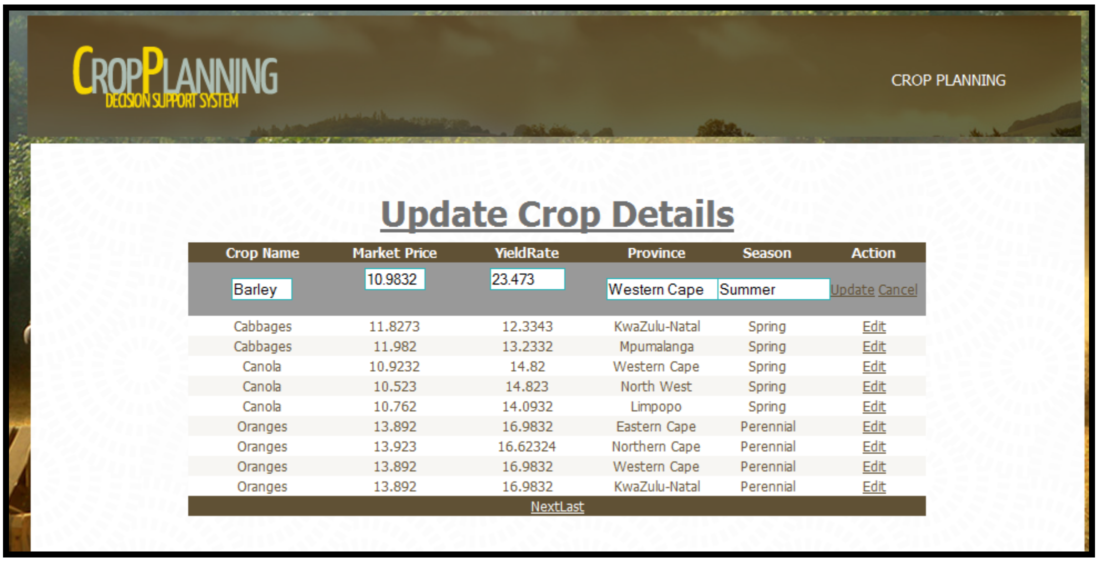

Figure 25: Updating crop details process

5.2.1.3. Deleting crop/ crop combination information

The crop details and crop combination information are deleted through Delete Crop/Crop Combinations functionality as shown in Figure 20 and remove in the crops and crop combinations table respectively. The Delete crop/crop combinations functionality is used by the administrator; it helps the administrator to delete crop and crop combinations. Once the administrator clicks on the functionality, it connects the administrator to a page where the administrator can perform these operations separately as shown in Figure 26.

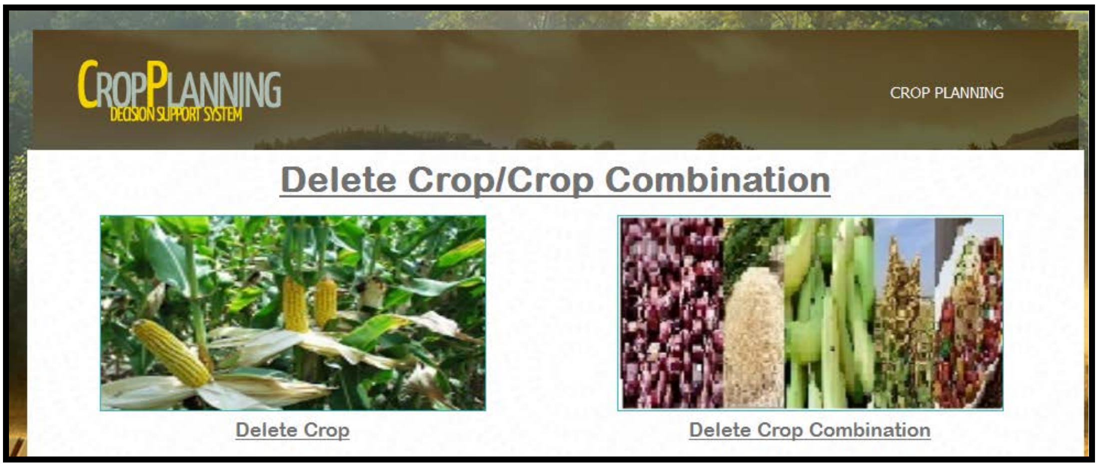

Figure 26: Delete Crop/Crop Combination page

If the administrator clicks on the delete crop function, Figure 27 is displayed but if the administrator clicks on the delete crop combination function, Figure 28 is displayed.

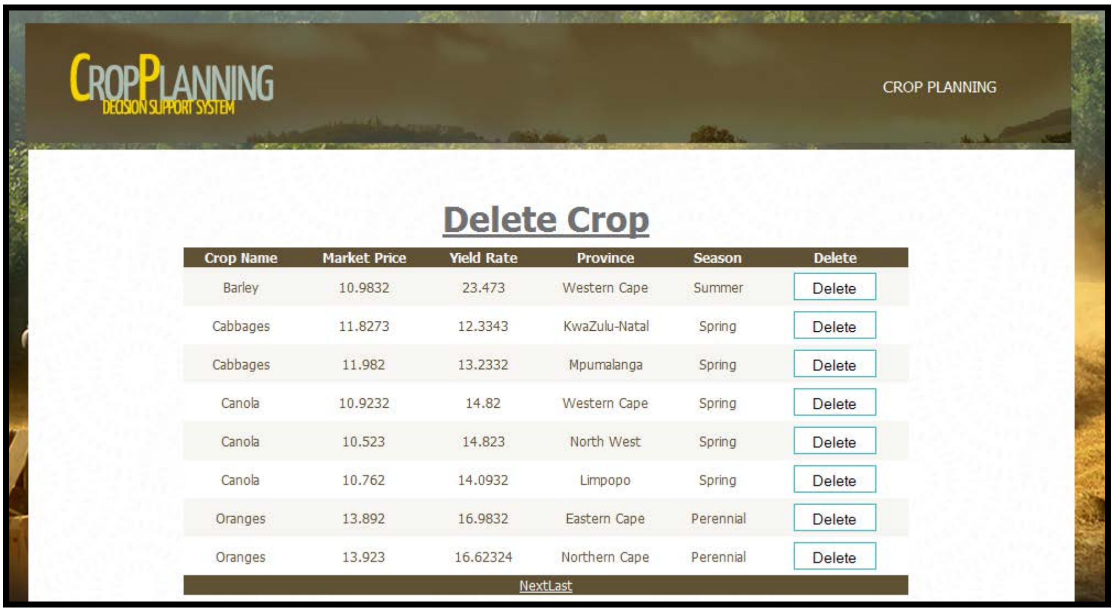

Figure 27: Delete crop details page

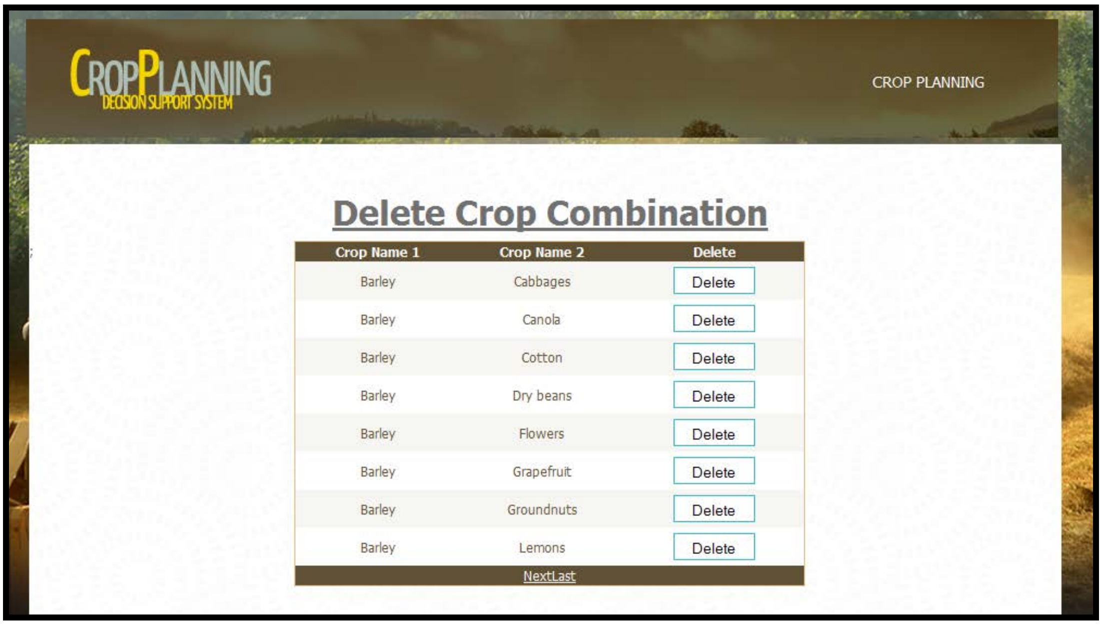

Figure 28: Delete crop combination details page

5.2.1.4. Registering and login user/farmer

The system provides the option to record new user as shown in Figure 18 using the register functionality. Register function in Figure 18 allows non-existing user to register and login into the system. Once a user clicks on the register function; Figure 29 is displayed on the screen.

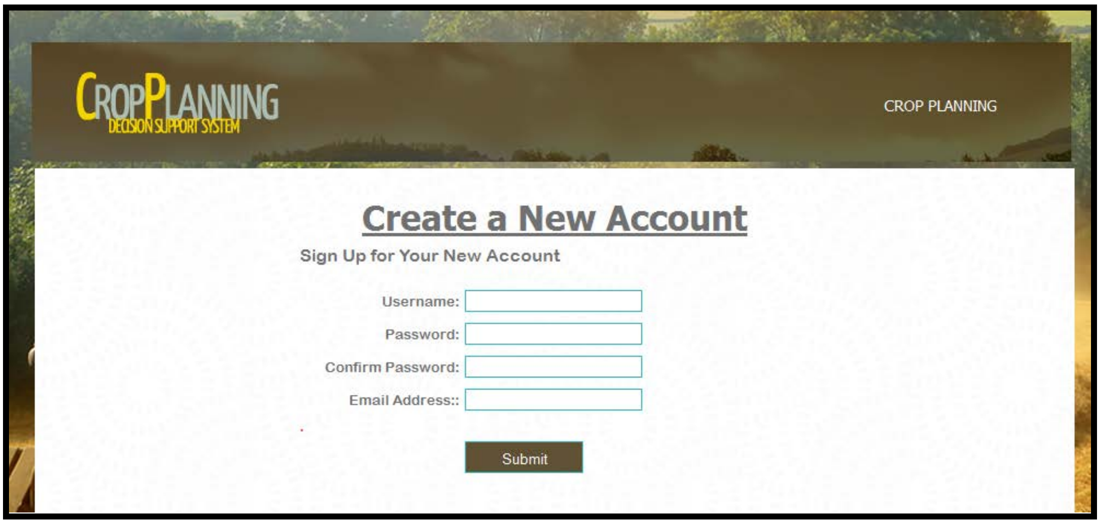

Figure 29: Register user page

5.3. How the CPLANNER works

The system is tested with a scenario where a household farmer has a working capital of R10,000 with the land mass of 1 hectare. The farmer chooses to plant crops that could be planted with cotton and maize such that the crop combination should be of order 3 i.e. the farmer wants to plant on a tri-cropped land. The farmer visits the system, and register as shown in Figure 18. The user then enters all his requirements as shown in Figure 19, then click on the button (view combination group) to view the crop combination group, the crop combination groups consist of crops that could be planted with the selected crops (cotton, maize). To view the number of possible crop combination that could be obtained, the farmer selects any of the crop combination group of his choice and click on the button (possible crop combination). Figure 30 shows the screen shot of the whole process.

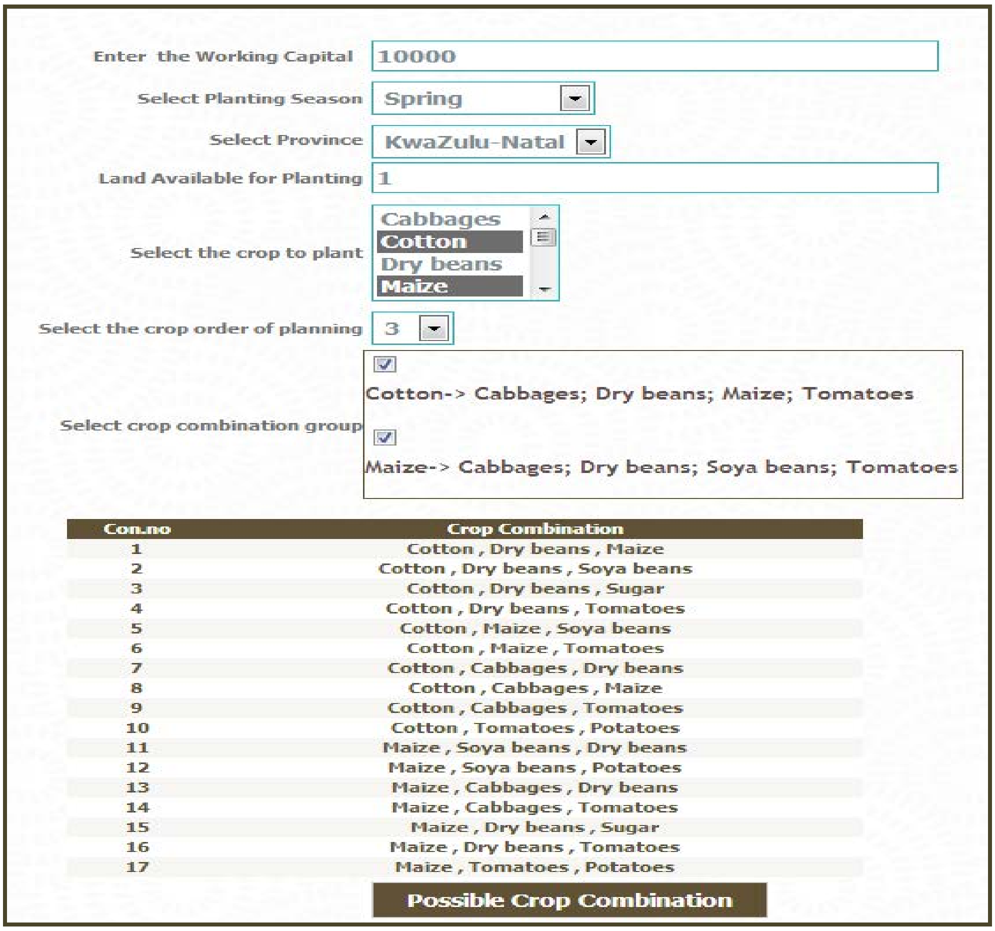

Figure 30: The Screen shot of the process page of the decision support system

The system allocates a land portion to each crop combination, working with the scenario where the farmer decided to choose both combination groups, the system produce the result in Figure 31. Figure 32 shows the best result of the optimization process while maximizing total crop production and minimizing total planting area.

Optimization

Con.no	Crop Combination	Allocated Land Potion
1	Cotton , Dry beans , Maize	0.0529411764705882
2	Cotton , Dry beans , Soya beans	0.0544834139681864
3	Cotton , Dry beans , Sugar	0.0551751168482547
4	Cotton , Dry beans , Tomatoes	0.0546802272946071
5	Cotton , Maize , Soya beans	0.0545767967254418
6	Cotton , Maize , Tomatoes	0.0529411764705882
7	Cotton , Cabbages , Dry beans	0.0529411764705882
8	Cotton , Cabbages , Maize	0.0553838335180744
9	Cotton , Cabbages , Tomatoes	0.0535227516257885
10	Cotton , Tomatoes , Potatoes	0.0529964867637148
11	Maize , Soya beans , Dry beans	0.0564644326910567
12	Maize , Soya beans , Potatoes	0.053910576210206
13	Maize , Cabbages , Dry beans	0.0529411764705882
14	Maize , Cabbages , Tomatoes	0.0550875681462448
15	Maize , Dry beans , Sugar	0.0538603684540516
16	Maize , Dry beans , Tomatoes	0.0548283920960852
17	Maize , Tomatoes , Potatoes	0.0544850090539479

Figure 31: The land allocation result

Net-Profit (ZAR)	Total Crop Production (Tons)	Total Land Utilization (ha)
995.340491905532	31.6222513740867	0.921219679278013

Figure 32: Output of the optimization process

5.4. Conclusions

This work suggests that the decision support system based on crop-mix optimization provides a useful means for optimal crop planning. The suggested approach can help subsistence farmers to efficiently utilize the available meager resources, including planting area, time and money. The approach combines indigenous farming with information technology to optimize crop production, support efficient planning and help subsistence farmers determine the possible combination of crops to plant on the same planting land year by year. On the basis of these, the analytical and conceptual model for the study has been specified. The system development process of the decision support system was also presented in this chapter. The limitations of the research method were also stipulated to avoid misinterpretations. This research study is shaped by the paradigm on the design, implementation and evaluation of the decision support system in the context of the identified problem in the crop planning domain.

CHAPTER 6

LIMITATION, RECOMMENDATION AND CONCLUSION

6.1. Study limitations

The availability of the required data was major constraint of this research. While designing the application; small scale farming was considered and in order to design the application for small scale farming, a detailed level of the crop data was required. This includes data such as the market price, yield rate, possible crop combination of all crops planted in South Africa. After liaising with the Department of Agriculture, Forestry and Fisheries, South Africa (DAFF) and Statistics South Africa (STASSA), the requisite data needed for the implementation was said to be unavailable. This necessitated the need to use fictitious values for the data required. Fictitious values were assigned to the required data and the assumption is that if the system can work perfectly with fictitious values, then it can work perfectly with the real values when provided. However, the results obtained from this study will be a guide to the bigger picture of the reality on the ground.

6.2. Recommendation for future work

Of course, applications are never finished and the application itself can be improved in many ways. The main recommendation is to take the application prototype and make a production version ready. The overall architecture of the prototype is correct, but specific implementation details can be improved. Furthermore, performance should be improved in order to run the application in a mobile environment. The application can also be extended in several ways. A first extension could be to implement an editor to guide the user in defining attribute values. This would reduce the number of errors that can be made. Furthermore, it provides more guidance to the user and therefore makes the application more users friendly. Another extension could be to implement the suggestions for the users. Besides improving the application itself, further investigation into specific extension could be conducted, especially extending the GDE3 algorithm for solving a crop planning decision under uncertainty. The researcher believes that fuzzy logic or interval probabilities could be useful to model uncertainties in the crop planning decision. This will produce a novel approach which combines differential evolution and fuzzy logic, for instance to deal with practical situations for which profit coefficients of agriculture are uncertain.

6.3. Conclusions

In this study, differential evolution algorithm was applied to crop allocation planning while taking farmers' decision-making process into account. The generalized differential evolution algorithm was applied to multi-objective optimization of crop planning in chapter 4. The results obtained in chapter 4 show that the performance of generalized differential evolution was very encouraging when compared to non-dominated sorting genetic algorithm (NSGA-II), which is one of the most popular evolutionary techniques. Chapter 4 also shows that the main objective of this study, which was to apply generalized differential evolution algorithm for optimal strategic decision making in crop farming system was achieved. More importantly in chapter 5, a decision support system based on the model obtained from the experiment performed in chapter 4 was developed.

The primary objective of this dissertation was to design a decision support system based on crop mix optimization that offers an effective way of supporting farmer to optimally plan for available quantity of agricultural input resources. As mentioned in chapter 1, this study has five specific objectives which were met. They are recalled for the sake of lucidities as follows:

a. Formulate a realistic crop planning decision task as a constrained multi-objective optimization model.
b. Apply generalized differential evolution algorithm to determine the optimum cropping pattern that will generate maximum net profit, maximum crop production and minimum land use for farmers.
c. Apply generalized differential evolution algorithm for optimal crop planning decision making.
d. Validate the performance of generalized differential evolution algorithm
e. Implement a prototype decision support system using generalized differential evolution algorithm.

The specific objective (a) above which was to formulate a realistic crop planning decision task as a constrained multi-objective optimization model was studied in chapter 4. The crop planning model formulation involved maximizing net profits, maximizing crop production and minimizing land area utilization when constrained by food demand, labour, capital and land availabilities on a farm. In chapter 5, the specific objective (b) and (c) was to apply generalized differential evolution algorithm for optimal crop planning, decision making that would generate maximum net profits, maximum crop production and minimum land area use for farmers. GDE3 was shown to be capable of modelling cropping pattern as a multi-objective optimization of maximizing total net profit, maximizing crop production and minimizing land area generated from farming. The best cropping pattern for each farmland modelled were determined by studying different cropping patterns. The models however are appropriate enough for farmers to make good decisions in relation to a total net profit expected from farming in the region.

The specific objective (d) in chapter 4 was to validate the performance of generalized differential evolution algorithm with performances of a widely used multi-objective optimization algorithm. NSGA-II was compared with GDE3 in optimizing the planting areas. The results show that GDE3 outperformed NSGA-II in terms of convergence and diversity. GDE3 was shown to be capable of solving multi-objective high dimensional problems with few control parameters. The advantage of traditional DE which is ease of use is also applicable to GDE3. GDE3 was shown to be capable of obtaining the global optimum of optimization problems like NSGA-II. GDE3 has the advantage of not being limited to linear problems, therefore can be used for a wider variety of applications, especially those that are not easy to linearize and methods that call for combined simulation optimization. GDE3 was shown to be successful at searching the feasible solution space for a complex cropping pattern that involves multi-objective and multiple constraints. The non-dominated solutions generated converge to Pareto optimal front. Also from the results, cultivating large area of land may not necessarily imply high profit for the farmers. A small area with a good cropping pattern can generate high profit.

Therefore crop planning is essential in a farming business and this model is a good choice for cropping pattern in an environment like South Africa.

The specific objective (e) in chapter 5 was to design a decision support system using generalized differential evolution algorithm. The decision support system helps farmers in the change of their production systems by exploring new management process through modelling. The use of this decision support system in a farm practice gives a critical role to farmers and decision makers an involvement in the farming process through a participative means. The design support system using decision-models provide mediation dialogs between farmers and decision makers to improve learning process and build common background. The model developed facilitates decision-making process, formulation by farmers and understanding farmers' encountered bottlenecks to adapt their practices by the decision makers. Through this dissertation, a contribution to the long tradition of research on crop planning at the farm level was made by proposing a modelling approach based on the farmer decision making process. This research opens a different perspective for developing farm specific decision support system that is based on simulating a farmer's decision making processes. Modelling and simulating the crop planning, decision making process should aid the designing of a farming, crop planning system that reconcile the adaptive capacities required for crop planning choices and the need to maintain cropping system robustness at the farm level.

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APPENDIX

Decision Support System Use Case Narration

<table>
<tr><td>USER CASE NAME:</td><td colspan="2">Register User.</td></tr>
<tr><td>USER CASE ID:</td><td colspan="2">USC-1.</td></tr>
<tr><td>PRIORITY</td><td colspan="2">High.</td></tr>
<tr><td>PRIMARY BUSINESS ACTOR:</td><td colspan="2">Household farmer.</td></tr>
<tr><td>OTHER PARTICIPATING ACTOR:</td><td colspan="2">N/A</td></tr>
<tr><td>DESCRIPTION:</td><td colspan="2">This use case describes the process of registering a user. The user requires an authentication before provided with an access into the system.</td></tr>
<tr><td>PRE-CONDITION:</td><td colspan="2">N/A</td></tr>
<tr><td>TRIGGER:</td><td colspan="2">This user scenario starts when the household farmer wants to use the system.</td></tr>
<tr><td rowspan="5">TYPICAL COURSE OF EVENTS:</td><td>Actor Action</td><td>System Response</td></tr>
<tr><td>Step 1: The household farmer wants to register.</td><td>Step 2: System asks the user to supply the required information.</td></tr>
<tr><td></td><td>Step 3: System provides a default text box for each of the required information.</td></tr>
<tr><td>Step 4: The household farmer completes the required information in the default textboxes</td><td>Step 5: To be sure that the household farmer enters the appropriate information in the default textboxes, the system validates the character of each text.</td></tr>
<tr><td></td><td>Step 6: Once the information</td></tr>
</table>

		provided by the household farmer is correct, the user successfully registers himself thereby having an instant-access permission to the system. A confirmation is shown to the household farmer.
ALTERNATE COURSES:	N/A	
CONCLUSION:	The use case concludes, when the household farmer receives the confirmation about the registration process.	
POST-CONDITION:	N/A	
BUSINESS RULES:	The user password should contain Alphabets (uppercase and lowercase), Numeric and Symbols	
IMPLEMENTATION CONTRAINTS AND SPECIFICATIONS:	The database must support the entry of alphanumeric characters.	
ASSUMPTIONS:	The user has modern browser installed.	
ASSERTIONS:	N/A	
USER CASE NAME:	Login user.	
USER CASE ID:	USC-2.	
PRIORITY	High.	
PRIMARY BUSINESS ACTOR:	Household farmer.	
OTHER PARTICIPATING ACTOR:	Administrator.	
DESCRIPTION:	This use case describes the process of logging into the system. The user requires an authentication before	

	provided with an access into the system.	
PRE-CONDITION:	The user must have registered.	
TRIGGER:	This user scenario starts when the household farmer wants to use the system after the successful registration process.	
TYPICAL COURSE OF EVENTS:	**Actor Action**	**System Response**
	Step 1: The household farmer wants to log in.	**Step 2:** System asks the user to provide his username and password.
		Step 3: To be sure that the user is valid, the system authenticates the user.
		Step 4: The user successfully authenticated. A confirmation is shown to the household farmer stating login successful.
ALTERNATE COURSES:	N/A	
CONCLUSION:	The use case concludes, when the household farmer receives the confirmation.	
POST-CONDITION:	N/A	
BUSINESS RULES:	The user password should contain Alphabets (uppercase and lowercase), Numeric and Symbols	
IMPLEMENTATION CONTRAINTS AND SPECIFICATIONS:	The database must support the entry of alphanumeric characters.	
ASSUMPTIONS:	The user has modern browser installed.	
ASSERTIONS:	N/A	
USER CASE NAME:	View Crop Combination Group.	
USER CASE ID:	USC-3.	

<table>
<tr><td>PRIORITY</td><td colspan="2">High.</td></tr>
<tr><td>PRIMARY BUSINESS ACTOR:</td><td colspan="2">Household farmer.</td></tr>
<tr><td>OTHER PARTICIPATING ACTOR:</td><td colspan="2">N/A</td></tr>
<tr><td>DESCRIPTION:</td><td colspan="2">This use case describes the process of viewing crop combination group.</td></tr>
<tr><td>PRE-CONDITION:</td><td colspan="2">The user must have registered.</td></tr>
<tr><td>TRIGGER:</td><td colspan="2">This user scenario starts when the household farmer wants to view crop combination group after logging in.</td></tr>
<tr><td rowspan="5">TYPICAL COURSE OF EVENTS:</td><td>Actor Action</td><td>System Response</td></tr>
<tr><td>Step 1: The household farmer wants to view crop combination group</td><td>Step 2: System asks the user to supply the necessary information such as province, working capital, planting season, list of crops, crop planting order and available land.</td></tr>
<tr><td></td><td>Step 3: System provides default textboxes and drop down boxes for each of information respectively.</td></tr>
<tr><td>Step 4: The household farmer completes the required information in the default textboxes and drop down boxes.</td><td>Step 5: To be sure that the household farmer enters the appropriate information in the default textboxes, the system validates the character of each text.</td></tr>
<tr><td></td><td>Step 6: The list of the crop combination group is shown</td></tr>
</table>

		to the household farmer where he selects the crop combination group of his choice.
ALTERNATE COURSES:	N/A	
CONCLUSION:	The use case concludes, when the household farmer views the crop combination group.	
POST-CONDITION:	The user must select a minimum of one crop combination group.	
BUSINESS RULES:	The user can select more than one group depending on his choice.	
IMPLEMENTATION CONTRAINTS AND SPECIFICATIONS:	N/A	
ASSUMPTIONS:	The user has modern browser installed.	
ASSERTIONS:	N/A	
USER CASE NAME:	View Possible Crop Combinations.	
USER CASE ID:	USC-4.	
PRIORITY	High.	
PRIMARY BUSINESS ACTOR:	Household farmer.	
OTHER PARTICIPATING ACTOR:	N/A	
DESCRIPTION:	This use case describes the process of viewing possible crop combination. In order to view possible crop combination, the user needs to select a crop combination group of his choice.	

<table>
<tr><td>PRE-CONDITION:</td><td colspan="2">The user must have registered.
The user must have selected crop combination group(s).</td></tr>
<tr><td>TRIGGER:</td><td colspan="2">This user scenario starts when the household farmer wants to view possible crop combinations after selecting the crop combination group(s) of his choice.</td></tr>
<tr><td rowspan="4">TYPICAL COURSE OF EVENTS:</td><td>Actor Action</td><td>System Response</td></tr>
<tr><td>Step 1: The household farmer wants to view possible crop combination.</td><td>Step 2: Using the list of crops in the selected crop combination groups, the system adopts a combinatorial algorithm to obtain the possible crop combinations.</td></tr>
<tr><td></td><td>Step 3: System arranges the result in the crop planting order provided by the user.</td></tr>
<tr><td></td><td>Step 4: The list of the possible crop combination is shown to the household farmer based on his selection choice.</td></tr>
<tr><td>ALTERNATE COURSES:</td><td colspan="2">N/A</td></tr>
<tr><td>CONCLUSION:</td><td colspan="2">The use case concludes, when the household farmer views the possible crop combination.</td></tr>
<tr><td>POST-CONDITION:</td><td colspan="2">N/A</td></tr>
<tr><td>BUSINESS RULES:</td><td colspan="2">N/A</td></tr>
<tr><td>IMPLEMENTATION CONTRAINTS AND SPECIFICATIONS:</td><td colspan="2">N/A</td></tr>
</table>

ASSUMPTIONS:	The user has modern browser installed.	
ASSERTIONS:	N/A	
USER CASE NAME:	Perform Optimization.	
USER CASE ID:	USC-5.	
PRIORITY	High.	
PRIMARY BUSINESS ACTOR:	Household farmer.	
OTHER PARTICIPATING ACTOR:	N/A	
DESCRIPTION:	This use case describes the optimization process to view the land allocation output, net-profit, total crop production and total land utilization result.	
PRE-CONDITION:	• The user must have registered. • The user must have selected crop combination group(s). • The user must have completed the process of viewing the possible crop combinations.	
TRIGGER:	This user scenario starts when the household farmer wants to view the land allocation output, net-profit, total crop production and total land utilization result.	
TYPICAL COURSE OF EVENTS:	**Actor Action**	**System Response**
	Step 1: The household farmer wants to view the land allocation output, net-profit, total crop production and total land utilization result.	**Step 2:** With the list of possible crop combinations produced by the system, the system extracts other essential parameter required in the crop planning model.
		Step 3: The parameters are then passed into the GDE3

		algorithm.
		Step 4: The result of the land allocation for each crop combination, net-profit, total crop production and total land utilization is shown to the household farmer based on his selection choice.
ALTERNATE COURSES:	N/A	
CONCLUSION:	The use case concludes, when the household farmer views the land allocation output, net-profit, total crop production and total land utilization result.	
POST-CONDITION:	N/A	
BUSINESS RULES:	N/A	
IMPLEMENTATION CONTRAINTS AND SPECIFICATIONS:	N/A	
ASSUMPTIONS:	The user has modern browser installed.	
ASSERTIONS:	N/A	
USER CASE NAME:	Add crop data	
USER CASE ID:	USC-6	
PRIORITY	High	
PRIMARY BUSINESS ACTOR:	Administrator	
OTHER PARTICIPATING ACTOR:	N/A	
DESCRIPTION:	This use case describes the process of adding new crop information. The process also describes the process of	

	adding new crop combinations.	
PRE-CONDITION:	The administrator must have registered.	
TRIGGER:	This user scenario starts when the household farmer wants to add new crop information.	
TYPICAL COURSE OF EVENTS:	**Actor Action**	**System Response**
	Step 1: The administrator wants to add new crop details and new crop combinations.	**Step 2:** System asks the administrator to provide the required information.
		Step 3: System provides a default text box for each of the required information.
	Step 4: The administrator completes the required information in the default textboxes.	**Step 5:** To be sure that the administrator enters the appropriate information in the default textboxes, the system validates the character of each text.
		Step 6: Once the information provided by the administrator is correct, the administrator successfully adds new crop information. A confirmation is shown to the administrator.
ALTERNATE COURSES:	N/A	
CONCLUSION:	The use case concludes, when the household farmer receives the confirmation about the process.	

POST-CONDITION:	N/A	
BUSINESS RULES:	N/A	
IMPLEMENTATION CONTRAINTS AND SPECIFICATIONS:	N/A	
ASSUMPTIONS:	The user has modern browser installed.	
ASSERTIONS:	N/A	
USER CASE NAME:	Update crop data.	
USER CASE ID:	USC-7.	
PRIORITY	High.	
PRIMARY BUSINESS ACTOR:	Administrator.	
OTHER PARTICIPATING ACTOR:	N/A	
DESCRIPTION:	This use case describes the process of updating crop information. The process also describes the process of updating the market prices and yield rates of the crops.	
PRE-CONDITION:	The administrator must have registered.	
TRIGGER:	This user scenario starts when the household farmer wants to update the crop information.	
TYPICAL COURSE OF EVENTS:	**Actor Action**	**System Response**
	Step 1: The administrator wants to update crop details.	**Step 2:** System asks the administrator to select which crop information is to be updated.
		Step 3: System provides editable textboxes for the data to be updated.
	Step 4: The administrator	**Step 5:** To be sure that the

	completes the required information in the editable text boxes.	administrator enters the appropriate information in the default textboxes, the system validates the character of each text.
		Step 6: Once the information provided by the administrator is correct, the administrator successfully update crop information. A confirmation is shown to the administrator.
ALTERNATE COURSES:	N/A	
CONCLUSION:	The use case concludes, when the household farmer receives the confirmation about the process.	
POST-CONDITION:	N/A	
BUSINESS RULES:	N/A	
IMPLEMENTATION CONTRAINTS AND SPECIFICATIONS:	N/A	
ASSUMPTIONS:	The user has modern browser installed.	
ASSERTIONS:	N/A	