ASSESSMENT OF VARIABILITY IN ON-FARM TRIALS: A UGANDA CASE

ODONG THOMAS LAPAKA
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Dedication

To my beloved mother Balbina Atyang.

Declaration

The work described in this dissertation was carried out in the School of Mathematics, Statistics and Information Technology, University of Natal, Pietermaritzburg, from February 2001 to December 2002, under the supervision of Dr. Peter Njuho.

The studies represent original work by the author and have not otherwise been submitted in any form for any degree or diploma to any University. Where use has been made of the work of others it is duly acknowledged in the text.

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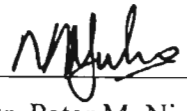
Student: 

Odong Thomas Lapaka

Supervisor: 

Dr. Peter M. Njuho

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Abstract

On-farm trials techniques have become an integral part of research aimed at improving agricultural production especially in subsistence farming. The poor performance of certain technologies on the farmers' fields known to have performed well on stations have been of concern. Traditionally, on-farm trials are meant to address such discrepancies. The main problems associated with on-farm trials in most developing countries are high variability and inappropriate application of statistical knowledge known to work on station to on-farm situation. Characterisation of various on-farm variability and orientation of existing statistical methods may lead to improved agricultural research.

Characterization of the various forms of variability in on-farm trials was conducted. Based on these forms of variability, estimation procedures and their strength have been assessed. Special analytical tools for handling non-replicated experiments known to be common to on-farm trials are presented. The above stated procedures have been illustrated through a review of Uganda case. To understand on-farm variability require grouping of sources of variability into agronomic, animal and socioeconomic components. This led to a deeper understanding of levels of variability and appropriate estimation procedures. The mixed model, modified stability analysis and additive main effects and multiplicative interaction methods have been found to play a role in on-farm trials. Proper approach to on-farm trials and application of appropriate statistical tools will lead to efficient results that will subsequently enhance agricultural production especially under subsistence farming.

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Chapter 1

Introduction

1.1 Background

Uganda enjoys a long agricultural research tradition, starting from the early colonial period when reputable and outstanding research stations at Kawanda, Namulonge, Serere and Entebbe were established. The faculty of Agriculture and Forestry(Makerere University) commenced agricultural research in 1957 (NARO, 2002). The impact on agricultural production of on-station research results has been slow. One of the reasons has been the lack of on-farm trials component in technology development and evaluation.

On-farm trials are experiments conducted on the farms, usually with the co-operation of and participation of the farmers (Njuho and Milliken, 1995). One of the major objectives of an on-farm trial is to test the performance of one or more improved technologies, usually in comparison with the farmer's own practices, under real farm conditions and under farmer management. Mutsaers, Weber, Walker and Fischer (1997) argued that trials conducted under maximum farmer management are the only valid way of testing new technology provided the farmers treat the trial fields in the same way as their other fields. In Uganda, national (Kawanda, Namulonge, Serere) and international(International Institute of Tropical Agriculture (IITA), International Center for Tropical Agriculture (CIAT), etc) agricultural research institutes have left the confines of their research stations to test new technologies under the small-scale farmer's conditions. It has become a policy of the research institutes in Uganda to test all their new technologies under the farmer's condition before giving recommendations to farmers (NARO, 2002). In on-farm trials,

scientist have to cope with experimental conditions which frequently have only a remote resemblance to controlled experimental conditions of the research stations.

Involvement of farmers and the use of their field/farms in agricultural research result in a high variability in the responses being measured (Mutsaers *et al.*, 1997) . Fielding and Riley (1998) stated that variability in responses resulting from many sources in the farmer's field is likely to be greater than that from sources in the research station. Large variability between and within farms complicates on-farm trial design and analysis, and provides major challenges to biometricians and data analysts (Nokoe, 1999; Oyejola, 1999). Based on the findings by Fielding and Riley (1998), Nokoe (1999) and Oyejola (1999), there is a need for understanding the nature of on-farm variability and the suggested remedial approaches.

Uganda is a very diverse country in terms of biophysical, cultural, socioeconomic and religious aspects. This gives rise to a large number of sources of variability encountered by scientists as they cross biophysical, cultural, socioeconomic and religious boundaries in the course of carrying on-farm trials. Trials conducted under the above mentioned conditions and under the farmers' management exhibit various forms of variability some of which are inherent. Research reports from Uganda (University theses and National Agricultural Research Organization (NARO) annual reports) indicate handling of these various forms of variability as a major problem in on-farm trials.

Although variability in on-farm trials has been cited as a major problem, less attention has been given to understanding the different forms (biophysical, cultural, socioeconomic, etc) of variability. Questions such as 'what are the non-experimental factors likely to affect my trials or over what area of my trial will a particular factor have influence?' remain unanswered. Knowledge of various forms of on-farm trial variation would enable researchers to focus their attention on effective methodologies. Such methodologies will consider the levels of variability in the design and analysis of data from on-farm trials.

Despite the realization of the usefulness of on-farm research, scientists were initially reluctant to carry out on-farm research due to doubts on publication of results from such

a highly variable experimental condition (Oyejola, 1999; Njuho and Chui, 1999). Many researchers are yet to be convinced of the statistical validity of on-farm trials (Njuho and Milliken, 1995; Nokoe, 1999). Some groups of researchers do not regard any research conducted on farms as scientific because many on-farm researchers disregard basic statistical principles (Njuho and Milliken, 1995). Most scientists in developing countries are trained for conventional on-station research and these are the methods they are applying in on-farm trials. The traditional on-station experimental designs such as randomized complete block design have been transferred to on-farm trials without any modification. A review carried out in Uganda (see section 5.1) indicates that 100% of the on-farm trials carried in the last five years (1997 - 2001) used the traditional Randomized Complete Block (RCB) design and all those experiments were analyzed using ordinary analysis of variance (ANOVA) methods. Mutsaers and Walker (1991) argued that scientists working under such a highly variable situation (on-farm) need reliable research methods and analytical techniques which are often outside the realm of conventional on-station research. As noted by Riley and Alexander (1997), as agricultural research becomes multidisciplinary, deficiencies in statistical methods are likely to increase with greater complexity and thus new approaches ought to be availed to researchers.

Many approaches for analysis of variability in on-farm trials have been developed/proposed (see Hildebrand, 1984; Njuho and Milliken, 1995; Hildebrand and Russell, 1996; Mutsaers *et al.*, 1997; Njuho and Chui, 1999). However, the main question that remains to be answered is 'why are those methodologies not being utilized by researchers especially those in the developing countries like Uganda?' Riley and Alexander (1997) pointed out that statistical methodology for use in participatory on-farm trials is available but not necessarily documented in a form easily used by non-statisticians. This conforms to a general statement made by Mclean, Williams and Stroup (1991) that researchers (practitioners) consistently report that the statistical literature to date falls well short of providing them with adequate guidelines for making informed choices of the methods to use. Whilst standard methodology is widely and clearly documented, statistical techniques for handling

on-farm trials is not catered for in the standard statistical training courses and literature on them is quite scanty and sometimes difficult to understand. Statistical methodologies should be availed to the researchers in a more tractable and easy to use form.

There is great need to motivate on-farm researchers to use new or improved approaches of analysis of data from on-farm trials. Demonstrating to on-farm researchers how these methodologies can improve their results can give them confidence in on-farm trial, statistical methodologies and encourage more researchers to get involved.

This study concentrated on identification and understanding of the various sources of variability that occur in on-farm trials and the methods of analysis of variability. For a proper understanding of the various sources of variability in on-farm trials we need statistical methods for analyzing the variability. We also looked at various statistical stools that can be used for analyzing data from such trials. Identification and understanding of the different sources of variability and their relative importance in on-farm trials together with the use of the right data analytical techniques can improve the efficiency of these trials. This will not only improve the quality of research work but also encourage more researchers to get involved in on-farm trials, which is the basis of development and adoption of new technologies.

Chapter 2 reviews literature on on-farm trials, with emphasis on variability, designs and analyzes. Chapter 3 deals with the characterization of the possible sources of variability in on-farm trials. Variability in agronomic and animal on-farm trials, levels at which variabilities occur and possible indicator variables to be measured are discussed. Finally the possible utilization of indicator variables are suggested. Chapter 4 focuses on procedures for analysis of variability in on-farm trials. A mixed model is proposed and discussed as an alternative method for assessment of variability in on-farm trials. The additive main effect and multiplicative interaction effect model (AMMI) and adaptability analysis (AA) are discussed as useful tools for handling variability in on-farm trials. In Chapter 5 we examine cases of on-farm trials in Uganda. An overview of the status of on-farm trials in Uganda is presented and briefly discussed. Three examples are used to

illustrate analysis of variability using the mixed model and the usefulness of AMMI and AA. Chapter 6 consists of the conclusions.

1.2 Objectives

Overall objective

To determine the causes of variability in on-farm trials and propose some methods of analysis of this variability.

Specific objectives

- To review the status of on-farm trials in Uganda.
- To characterize the different sources of on-farm variability and their causes.
- To assess methods of analysis of variability in on-farm trials.
- To provide illustrative examples on the analysis of variability of on-farm trials.

Chapter 2

Literature Review

2.1 On-farm research

On-farm research is conducting an important part of research together with farmers in their own environment with aim of finding adaptable and sustainable solutions to their production constraints. On-farm research has two major components which are on-farm trial and diagnosis (see Mutsaers *et al.*, 1997; Oyejola, 1999). Diagnosis help in stratification of farming environments and regions and identification of farmers' production problems so that appropriate solution can be found (Mutsaers *et al.*, 1997). On-farm trials are therefore a component of a broader on-farm research. Most literature treat on-farm trials under the broader heading of on-farm research. There are many reasons for conducting on-farm trials, and most of them are presented under the importance of on-farm research (see Sumberg and Okali, 1988; Mutsaers *et al.*, 1997; Janice 2000 and Francis, 2001). On-farm trials are classified according to the level of participation/involvement of the farmer and the researcher. The categories include researcher designed and managed; researcher designed and researcher-farmer managed; researcher designed and farmer managed, and farmer designed and farmer managed (Okali and Farrigton, 1994; Coe and Franzel, 1995; Riley and Alexander, 1997). Mutsaers *et al.*, (1997) pointed out that the above classifications of on-farm trials are more confusing than useful and stressed that the basic principles of on-farm trial is that the degree of farmers' management should be maximized.

2.2 Variability in on-farm trial

The high degree of variability in the responses of on-farm trials has been reported by many authors (Njuho and Milliken, 1995; Fielding and Riley, 1997; Mutsaers *et al.*, 1997; Njuho and Chui, 1999 and Nokoe, 1999). The fact that conditions on the farms are very variable owing to different degrees of farm management and other factors greatly contribute to high variability in on-farm trials (Njuho and Chui, 1999). Mutsaers and Walker (1990) pointed out that the two main sources of variation in on-farm trials are between farms or between sites variation and within-farm or within site variation. Between-farm or between site variation is due to differences in such factors as site fertility, shading, temperature, humidity, rainfall, crop disorders, etc, as well as differences in planting dates and other basal treatments often lumped together as 'management'. Within-farm or within site variation can result from farmers carrying out operations such as weeding unevenly over trial plots, localized incidence of crop damage, micro-variation of soil conditions, shade and premature harvest of part of the plots (Mutsaers and Walker, 1990; Mutsaers *et al.*, 1997). In the case of animal trials within farm variation can be due to differences in feeding, housing or the management of individual animals. Farm differences (variation) arise from social, cultural and economic factors as well as from biophysical factors such as soils, vegetation and climatic influences (Hildebrand 1984). Conducting experiment in the farmer's field/farm enables the researchers to monitor variation in climate, soils and biology (Collinson, 1987). With the farmer's participation in the trial, researchers can assess the effect of the interaction between treatments and the farmer's management. Collision (1987) further argued that the flexibility in management practice is perhaps the major small farmer's strategy for managing climatic and resource variation, and hence it should be carefully considered in on-farm trials. Nokoe (1999) echoed the same sentiment when he stated that high variability is a natural and indeed a desirable consequence of on-farm trials. The high variability in on-farm trials posed problems in the design and analysis of on-farm trials and led to the belief among some researchers that on-farm trials cannot be planned (Nokoe, 1999).

Effect of variability on estimation of treatment effects

Treatment effects in on-farm trials depend heavily on farmer practices and farm location (interaction between treatment and environment). On-farm trials are often criticized for their lack of precision due to uncontrollable factors which overshadow treatment effects (Nokoe, per. com). By using farm (site) and plot/animal as covariates, it is possible by use of a combination of standard statistical techniques to separate treatment effects from environmental effects, and more importantly to show how the environment may influence the treatment effects (Mutsaers and Walker, 1991). In theory variation between farms can be accounted for by increasing the number of replications between and within farm. On-farm trials are often not replicated within farms. Thus the interaction between treatment and farms end up being part of the error term. Important information on farm differences would be lost unless the covariates are recorded and statistical techniques are used to separate a relevant part of the interaction from the rest of the error term (Mutsaers and Walker, 1990). Nokoe (1999), suggested two approaches for solving the problem of high variability in on-farm trials: (1) use of appropriate experimental design that takes between and within farm variability into account and (2) examining the data sets from such trials and searching for suitable models that best fit the data.

2.3 On-farm trial designs and sizes

Trial designs

The experimental designs used in on-farm trials belong to the class of nested designs (plot/animal nested within farm and farm nested within village), and more often there are no replications within the farm in order that the burden and interference on the farmers' routine farming activities are kept minimum (Korie and Okechukwu, 1999). Experimentation on the farmers' field/farm poses problems not encountered on experimental stations (Fielding, 1990). One main problem with on-farm trials is the limit on the number of treatments allowable per farmer's field or site. It is often recommended that where there is a high degree of involvement of farmers, the number of treatments should not ex-

ceed six so that farmers do not lose sight of the purpose of the trial (Mutsaers *et al.*,1997; Oyejola, 1999). This puts constraint on the type of design and number of replications. Although the Statistical Service Center (2001a) accepted that a large number of treatments leads to complexity in design, which in turn can lead to partial failure of the trials, they observed that the experiments are time consuming and hence costly and it would often be wasteful to go for an on-farm trial with just three or four treatments. The Statistical Service Center (2001a) suggested that a complex study could be split into simpler related experiments that may differ in their level of farmer participation.

Another issue of concern in on-farm trial design is the definition of controls or standard treatments. In on-farm trials the control is often the farmer's normal practices, which vary from one farmer to another (Njuho and Milliken, 1995; Mutsaers *et al.*, 1997; Statistical Service Center, 2001a). For example, local varieties or practices vary between farmers and seasons. Where the objective is to compare new varieties with the local one, each farmer's local variety can be used as control, and where there is need to standardize across farms, a typical practice or system may be used (Oyejola *et al.*, 1999). Lack of a common control makes it difficult to evaluate the treatment effects efficiently across farms (Njuho and Milliken, 1995). The farmer's normal practise cannot be regarded as a control in the usual sense, i.e. as a baseline treatment for the whole experiment against which other treatments are compared. The farmer's normal practice will be useful as a baseline for each farmer, but the researcher may also wish to have a common baseline in addition (Statistical Service Center, 2001a).

All basic and extended designs are possible in on-farm trials (Nokoe, 1999). The choice of a design to be used on a given farm depends on the nature of the on-farm variation to be controlled and number of treatments involved. Neeley *et al.* (1991) stated that the most commonly used design in on-farm trials was randomized complete block, and that row and column designs were not recommended for 'general use' in on-farm trials. However, results from the study done by Fielding (1990) suggested that row and column designs should be used as alternatives to randomized block designs as they can improve precision

by about 10% compared to randomize block designs. Fielding (1990) further argued that as row and column designs are relatively easy to design and can be analyzed by a larger range of computer software packages than is available for spatial analysis, they are doubly suitable where statistical support is limited. Nokoe (1999) also noted that most on-farm trials have complete or incomplete block structures and have single or multi-factor treatment structures. Split-plot and blocked designs, particularly incomplete block designs, give the flexibility needed to accommodate farm/site conditions and treatment management factors, which often play a major part in the researchers' decision on the design to be used (Collinsons, 1987). As 'preventive' approach, Nokoe (1999) illustrated some useful designs for on-farm trials. The designs included augmented block designs, confounding and fractional replication schemes, latin squares and related designs, and optimal row-column designs. Mutsaers *et al.* (1997) recommended the use of stepwise and criss-cross designs. First order designs can be used for exploratory trials involving many factors. Where there are many treatments to be tested, factorial replication and confounding schemes are useful when the treatments have a factorial structure (Oyejola, 1999). Set up/down schemes described by Mutsaers *et al.* (1991) can also be used to reduce the number of treatments. A combination of confounding and step up/down can also be used.

Replication

For precise treatment comparisons there is need for sufficient replication - but at what levels? It is usually preferable to have more farms and fewer repeats of treatments per farm rather than fewer farms and more replications within the farm. Maximizing the number of farms is generally more important in on-farm trials than replications within farm (Mutsaers *et al.,* 1991). Consequently in on-farm trials, it is frequently the case that there are many farmers but each farmer has only one replicate of a given set of treatments (Statistical Service Center, 2001a). Njuho and Chui (1999) suggested that for researcher-designed and farmer managed type of on-farm trials, at most two replications per farm is needed to protect against missing values within a farm. The problem with

having no within farm replication is that the farm-by-treatment interaction variation is then normally used as the random (or residual) variation. However, the treatment effects may really be different for the different farmers, and understanding such interaction e.g. which treatments are most effective for which types of farmers, may be an objective of the research. In such a case one would like to distinguish between interaction and residual and having some replication within the farm allows this distinction. The Statistical Service Center (2001a) suggests that consideration be given to a design where each farmer repeats a single treatment. Alternatively, several (ten or more) farmers could repeat one treatment not necessarily the same one through out. Fielding and Riley (1998) concluded from their studies in Jamaica, that when only a few trials can be done, as many within farm replications as possible must be included, but when 15 or more trials are used there is little to be gained from replication. Several authors have advanced very strong practical argument for the use of few within farm replications in on-farm trials (Mutsaers and Walker, 1990; Mutsaers *et al.*, 1991; Stroup *et al.*, 1991; Mutsaers *et al.*, 1997,). According to Hildebrand and Russell (1996), the number of farm environments that need to be included will vary depending on the number of factors, but 15 to 20 should be adequate in most cases.

Plot sizes

The literature suggest that plot sizes for on-farm trials should be larger than those in on-station trials (Collisons, 1987; Mutsears *et al.*, 1997; Fielding and Riley, 1998). Fielding and Riley (1998) noted that the sizes of the plots often must be large to incorporate the possibilities of greater spatial variation caused by soil heterogeneity or interference to the growth or yield of the plot. However, Collinsons (1987) argued that plot sizes should be larger in a closer approximation to field scale.

2.4 Nature of data from on-farm trials

The type of data to be collected depends on the objective(s) of the experiment. Different types of trials require different types of data to be collected, and researchers should carefully spell out at the inception of the trial the type of data to be collected and most importantly how they will be used in the analysis (Mutsaers, 1991). The higher the degree of farmer decision making the more need there is to observe and measure non-treatment conditions in the trials. In on-farm trials data in most cases have hierarchical or multilevel structure, i.e. data is collected at different levels. For example, there can be information at village, farm and plots or animal level (Statistical Service Center, 2001b).

In agronomic trials and at plot level, the relevant agronomic variables are crop yields, stand counts, weed scores, farmers' relative assessment (e.g. better or worse), input variables (including labor) (Mutsaers, 1991; Mutsaers *et al.*, 1997). In animal on-farm trials and at animal level important variables include animal's breed, weight (birth, weaning or live weight), growth rate, feed gain ratio, reproductive performance (kidding or calving rate, twining rate, live birth, etc), milk yield, mean milk yield per lactation, body condition scores, feed and water intake, mortality rate, counts (faecal egg counts, tick counts, etc), packed cell volume (PVC), worm burden, blood sample test result (positive or negative, infected or non infected) (KARI, 1994). Farmers' assessments (ordinal) at the treatment level are also appropriate. At farm level, soil characteristics (such as texture, pH), management practices, history of experimental site (field), vegetation, farmer's demographic data, management of animals (housing, feeding, health care, breeding programme etc) are useful (Ames and Ray, 1983; Mutsaers, 1991; Mutsaers *et al.*, 1997). Rainfall, temperature, humidity socioeconomic data (labor and input costs, prices of commodities) are needed at village/environment level (Mutsaers, 1991; Mutsaers *et al.*, 1997). Data on covariates appropriate to the objective of the trials must be selected. Such data may be collected through surveys or other studies (Oyejola, 1999).

According to Njuho and Chui (1999) on-farm trials are characterized by missing observations, unbalanced data and some inflicted variations due to improper management

of the trials. They recommended that efforts should be made to understand data coming from such situations. Riley and Fielding (2001) noted that data from on-farm participatory research are of poor quality and parametric assumptions might not always hold. On the type of data to be collected, Riley and Fielding suggested that the limited resources and time should be spent on the collection of data that characterize the environment and farmers practices and that accuracy of measurement should not be over emphasized in on-farm trials. Jiggins (1989) mentioned reduced quantity of numerical data and increased quantity of fuzzy data among the disadvantages of participatory on-farm trials.

Most authors have not been clear on who should collect data from on-farm trials although their reports indicate collective efforts of researchers, extension agents and farmers during the trial period. Eremie *et al.* (1991) stated that most research institutes in Nigeria prefer to send their own technicians to collect data from on-farm trials than allowing agricultural project development officers and subject matter specialist to do it. The use of field assistants to monitor the field and collect management data was reported in maize trial in Benin (Versteeg and Huijsman, 1991). The harvesting of the crop to determine the yield is always done by the farmers together with field assistants or extension agents.

2.5 Analysis of on-farm trials

Because of the peculiarity of data collected from on-farm trials, care must be taken not to apply the conventional methods incorrectly to analyze and interpret such data (Oyejola, 1999). Riley and Fielding (1998) demonstrated how non-parametric methods could be used to analyze some data that may not lend themselves to the usual analysis of variance (ANOVA). Oyejola (1999) listed the following methods for analyzing on-farm trial data: Analysis of unbalanced and non-orthogonal designs; Analysis of multiple levels of variation; Analysis of repeated measures; Categorical data analysis (using procedures like CATMOD in SAS); Economic analysis and farmer assessment. In what he described as 'Surgical' approach Nokoe (1999) enumerated a number of options for handling data from on-farm trials which included graphical analysis as in modified 'stability' analysis (Hilde-

brand, 1984) and incorporation of a environmental or site index in a conventional analysis of variance (Mutsaers *et al.*, 1997); Multiplicative interaction modelling (Milliken and Johnson, 1989; Guach (MATMODEL), 1993 and Eauwijk, 1995); Correspondence analysis; Regression modelling with covariates; Mixed model and Meta-analysis. Nokoe (1999), suggested combined use of meta-analysis and mixed modelling as a very strong surgical option for analysis of unplanned multi-site trials. Njuho and Milliken (1995) demonstrated how a mixed model approach can be used as an alternative to meta-analysis for comparing one treatment to possibly different controls. Grouping of farms/site as means of reducing variability in analysis of on-farm trial data by monitoring changes in Coefficient of Variation (CV) has been discussed at length by Njuho and Chui (1999). Conventional analysis of variance (including MANOVA) may be appropriate when the usual assumptions are valid. When data are categorical, generalized linear modelling enables analysis of a wide range of responses (nominal, ordinal and binary). Mixed model analysis allows for recognition of the multiple levels of variation. It also allows for a distinction between fixed factor effects (treatment effects etc) and random factor effects (effects of random errors, block, farms, environments and their interaction with treatments). This method allows one to combine experiments, which would otherwise have been conducted and analyzed separately (Oyejola, 1999).

Participatory on-farm trial is a very important component of applied research since it leads to finding adaptable and sustainable solution to the farmer's production constraints. However, involvement of farmers in these trials results into high degree of variability which most researchers are not well equipped statistically to handle. Variability in on-farm trials come from many sources which are often not very well understood by most researchers and data analysts. As a result, the design and analysis of on-farm trials are often more complicated and needs special statistical attention as compared to on-station trials.

Chapter 3

Characterization of variability in on-farm trials

3.1 Introduction

Studies related to on-farm trials take different forms which depend on the scientists' interest. For instance an animal scientist may be interested in developing a feeding technology for a particular area. The choice of the experimental material would depend on availability, knowledge and willingness of the farmers in that area. An agronomist may also wish to conduct an on-farm trial to investigate the performance of a particular technology compared to the farmers' one. Again the choice of experimental material would depend on what would be readily available in the region of study. The highlighted situations involve different sources of variability some of which are inherent. The term 'variability' is viewed in the context of farmer's knowledge, socioeconomic status, cultural practices and the general environment within which he or she lives. High variability therefore exist both between farmers and between and within the farm environments. Different groups of farmers and environments would have different constraints which require different solutions or even different solutions for the same constraints. Uganda like most developing countries in the tropics is diverse in climatic, biophysical, social, cultural, religious and socioeconomic aspects. Farmers in different parts of Uganda have different farming systems characterized by the type of crops, crop combination and animals kept on the farm. Farmers differ not only in farming practices but also in educational status, wealth, and

other cultural and socioeconomic aspects. With a large number of forms of variability from many sources and possibility of overlap between them there is need to point out clearly the sources of variability that are likely to be encountered in on-farm trials so that the design, analysis and interpretation of such trials is simplified.

3.2 Variability in an agronomic on-farm trial

The high variability in agronomic on-farm trials is due to various sources which can be grouped broadly into four categories: plant genotype, management practices (past and present management practices), socioeconomic and biophysical environment (see Figure 3.1). Each of these broad categories has components which contribute to the total variability either directly or indirectly. The importance of the contribution of each sources of variability will dependent on the type of trial under consideration. For instance biophysical factors may have more influence on on-farm trials involving soil conservation methods than plant genotype.

A stochastic relationship between the response variable Y and the effects of the different sources of variability can be given as:

$$Y = f(G, E, M, S) + \varepsilon \tag{3.1}$$

where f is a general mathematical function which can take any form, G is the effect of the plant genotype, E is the effect of the biophysical environment of the crop, M is the effect of past and present management, S is the effect of socioeconomic factors and ε is random error. The plant response is a function of the effects of genotype, environment, management, and socioeconomic characteristics of the farmer and the farming community. The plant genetic composition, environmental conditions, management practices and socioeconomic disparities all contribute individually or collectively to the total variability in plant responses. These sources of variability are briefly discussed in the next section.

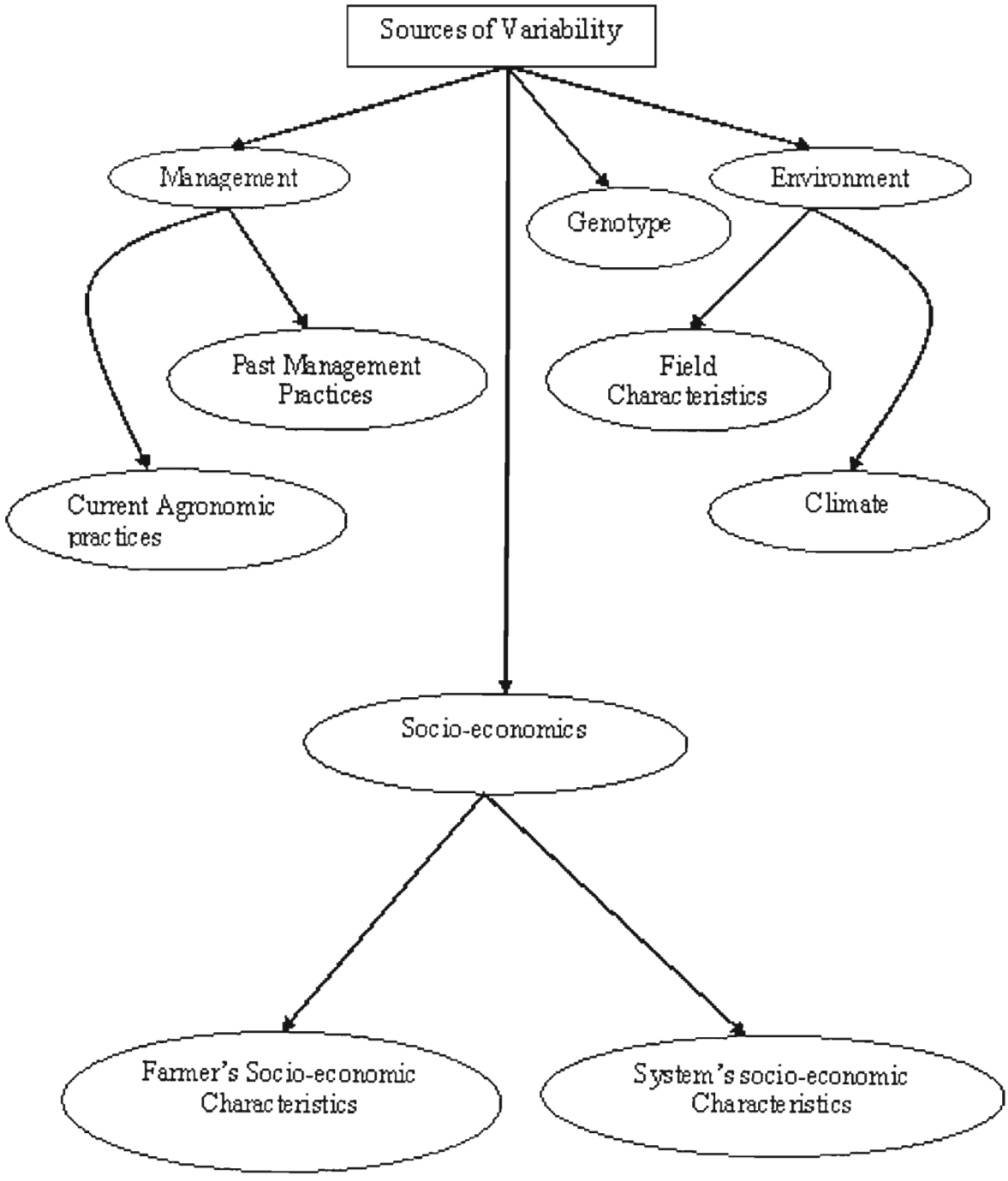

Figure 3.1: Schematic illustration of agronomic variability

3.2.1 Plant genotype

Plant material used by farmers are often of different genetic composition and this leads to variation in plant responses to both experimental and non-experimental factors. Plants of different genotype vary in their response to pests and disease attacks, nutrient deficiencies and other biophysical stresses such as extreme temperatures and humidity.

3.2.2 Biophysical environment

In this study biophysical environment consists of field characteristics and the climatic conditions of the area of trial. Possible causes of variation of the fields are:

- Physical, chemical and biological properties of the soil
- Topography
- Susceptibility to pest and disease infestation
- Vegetation
- Field size

Greater variability is brought about by differences in soil types. Different soils respond differently to rainfall and management inputs. For example, heavier fertile soils respond well to high rainfall levels giving good yields but these areas show low productivity under poor rainfall conditions. Chemical and biological properties of the soil are more prompt to variation as compared to the physical properties to the extent that they can even vary within the same field. This is due to the fact that chemical and biological characteristics of the soil are easily affected by management practices. Soil characteristics can vary both within and between farms. According FAO Uganda has about 40 different soil types (FAO-UNESCO, 1978). However, in terms of agricultural productivity there are six categories: soils of high to very high productivity, soils of moderate productivity, soils of fair productivity , soils of low productivity, soils of negligible productivity and soil nil productivity (Anon, 1996).

Variation in topography mostly occurs between farms in different locations e.g. different villages, counties, districts, regions or agro-ecological zones. Topographical variation can also occur within the same location. The variation as a result of topographical differences is much high for on-farm trials that cover a large part of the country. Uganda's land form comprise of plateaus, highlands, mountains, rolling hills and flat lands. Most of the country consists of plateaus between which there are valleys. The above differences in topography can have great influence on the results of on-farm trials.

Vegetation also leads to variation in the responses of the fields since it can influence the amount of shading experience by the crops, chemical, physical and biological characteristics of the soil and occurrence of diseases and pests. Differences always exist between fields due to the types and amount of vegetation in or surrounding the fields. Uganda has ten (10) different types of vegetation: high altitude moorland and health, medium altitude forests, forest/savanna mosaic, moist thicket, woodland, wooded savanna, grass savanna, bushland and dry thicket, swamps (wet lands) and cultivation communities (Anon, 1996). With increasing human activities there are too many changes in vegetation even within those areas with the major types of vegetation.

Different fields sometimes have different susceptibility to pest and disease infestation. Fields with a lot of weed seeds in the soil tend to be dominated by weeds and vice versa, and the amount of weed/weeds sometimes depends on the method used to control weed in the past. Diseases and pests sometimes move from one field to another implying that fields which are more closer to the source of diseases and pests are prone to attack than the ones which are far away. Some diseases are soil borne. Thus field which has the disease causing agent is likely to suffer from disease attack as compared to the one without. The effects of pests and diseases usually result in very high variability in agronomic on-farm trials.

The differences in farm temperatures, wind speeds, humidity, rainfall and solar radiation is due to differences in climate which varies from one place to another. The differences in climate mainly occurs between places which are far apart. Using rainfall

received in an area as the most important climatic variable, Uganda is classified into five major climatic zones: lake Victoria, Karamoja, western Uganda, Acholi-Kiyoga and Ankole-western Uganda zones. These rainfall zones are defined more in terms of similarities of rainfall distribution rather than by amount of rainfall. According to Scoones (1998) variation in rainfall is the primary factor influencing pattern of crop out put in dry land areas. The variation in climate exists between farms as well as between and within seasons.

3.2.3 Management

The participation of the farmers in on-farm trials lead to variation due to their different management practices. These practices differ due to the fact that the farms are on different soils, have different environmental conditions and that the farmers' levels of understanding are different. Management can vary both between and within farm (a farm can treat different plots differently). The variation in management can be due to past or present agronomic management practices.

Past management practices (Cropping history)

Fields are often put to different use by farmers and even when they are used for the same purpose the management practices might be different. Variation in past management can stem from differences in use of inputs such as fertilizers, pesticides, new crop varieties, etc. Variation can also arise from differences in past cultural practices such as fallowing, crop rotation, mulching, intercropping, erosion control and other soil conservation methods. The same cultural practice can be performed in different ways by the different farmers. For example other farmers have different fallow periods. The crops used for crop rotations are always not the same or the same pattern is not followed by all the farmers. All the differences in past cropping history have different effects on the fields thus leading to high variability in agronomic on-farm trials.

Present agronomic management practices

In farmer managed on-farm trials, agronomic practices which are not part of the treatment are supposed to be entirely under the management of the farmer without interference from the researchers (Mutsaers *et al.*, 1997). Differences are bound to occur in planting dates, land preparations, pest and disease control methods and the time, frequency and quality of weeding since each farmer would do it his/her own way. Some farmers may decide to use different crop varieties from others or some may apply fertilizers while others do not. All these differences lead to high variability in data collected from on-farm trials.

3.2.4 Socioeconomic factors

Variation in educational background, ethnic or cultural background, age, sex and occupation exist among farmers irrespective of their biophysical environment. The farmers can be classified as commercial, subsistence, progressive or part time farmers depending on the time and resources they allocate to farming as well as the purpose of production. Access to cash and credits vary amongst farmers depending on whether a farmer has other sources of income or has collateral security (to enable him/her acquire loan) or belongs to a farmers' organization. Wealthy farmers can use hired labor while poor ones have to depend on family labor. Land ownership, cattle ownership, labor availability, access to cash and ownership of tools can all be expected to have direct impact on variability (Scoones, 1998). Health and living conditions of the farmer and his family also vary greatly and this affects other farm operations.

Socioeconomic variations also exist between the farming communities. There are variations in policy, power sources, water sources, market, schools, hospital and other infrastructures. Socioeconomic characteristics do not affect crop response directly but indirectly through their effects on other factors such as present agronomic practices as well as past management practices which in turn affect field conditions.

3.3 Variability in animal on-farm trials

Variability in animal on-farm trials can be broadly classified into two: environmental and genetic variations.

3.3.1 Genetic variation

Genetic variation stems from the different breeds (exotic, cross or local) which are present on a given farm. The different breeds differ in growth rates, reproduction, productivity (milk, meat, eggs, wool etc), tolerance to adverse conditions (pests, diseases and unfavorable climate) etc. Variation also exist among individual animals of the same breed (age, sex, body condition scores, weight, size and shape). The above differences affect animal responses to management practices. Some of the individual animal characteristics are as a result of interaction between genotype and environment. Thus genotype variation affects the animal responses directly and indirectly through interaction with the environment. Genotypic effects variation together with their interaction with the environment result in variation among animals (see Figure 3.2).

3.3.2 Environmental variation

Animal environment can be divided into biophysical and managerial environments. The biophysical environment of the animal consists of climate, soil characteristics, topography and vegetation. Variation in climate is due to differences in rainfall (amount, distribution and pattern), temperature, humidity, wind and solar radiation. The main components of managerial environment are feed, water supply, housing, management of animal health and other husbandry practices. Biophysical factors such as climatic conditions, topography, soil characteristics and vegetation affect animals both directly and indirectly. Direct effects include the effect of temperatures, humidity, solar radiation, on the growth and development of the animal while indirect effects include environment-genotype interactions. Animal environment in this case is the sum total of all external conditions and circumstances that affect the health, well being as well as productive and reproductive

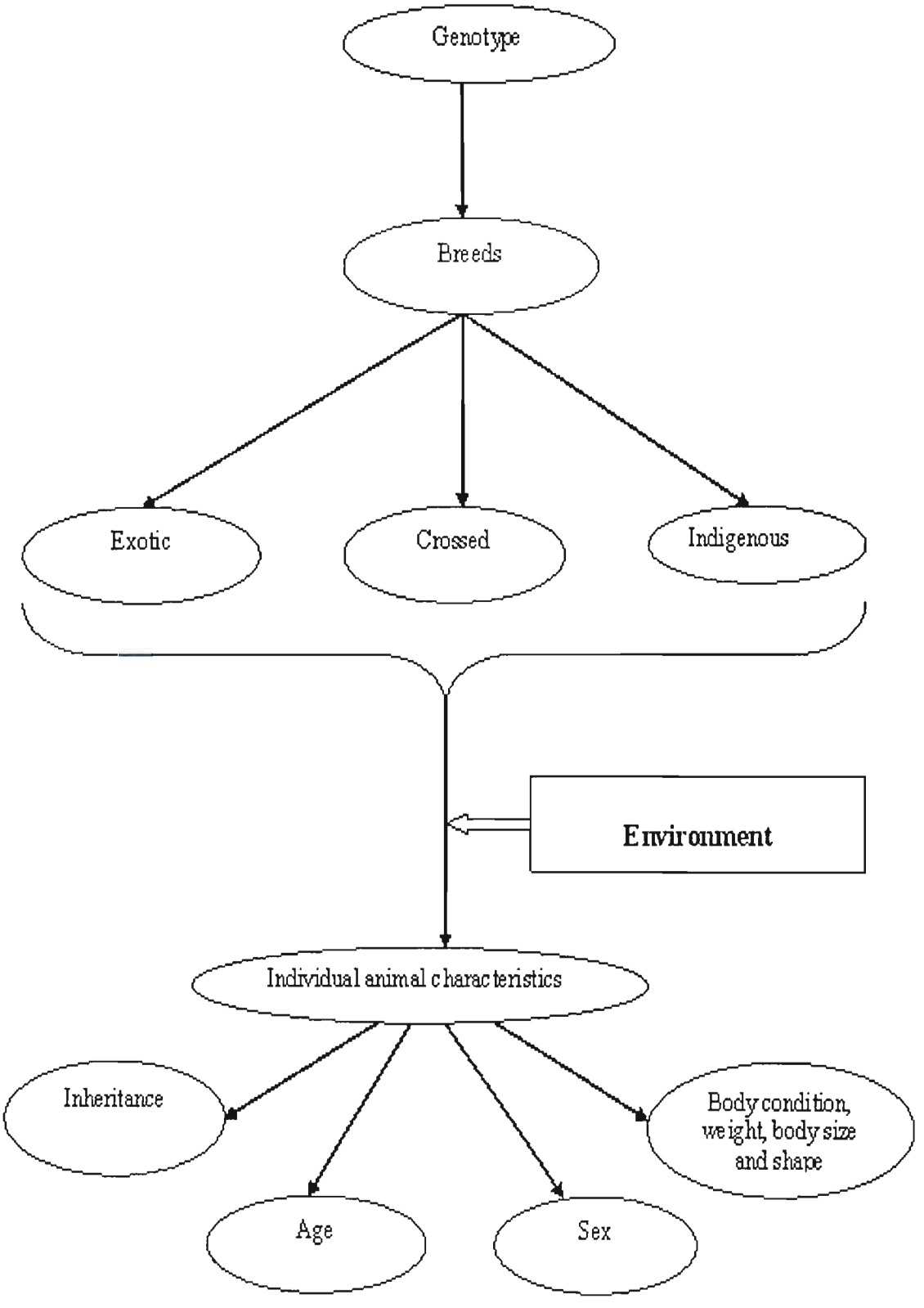

Figure 3.2: Schematic illustration of genetic variation

performance of the animal.

3.3.3 Management variation

The domestic livestock performance is strongly influenced by biophysical environment, management system and husbandry practices (Carpenter, 1998). Small scale farmers in developing countries do very little to alter the biophysical environment of the farm animals but try to improve the production of their animals through various management practices. Due to various socioeconomic factors the level and type of management practices carried by these farmers vary greatly. Management practices are aimed at improving animal health, nutrition, housing, and breeding. We can therefore break management into health management, feeding and water supply, housing, breeding and other husbandry practices (Figure 3.3).

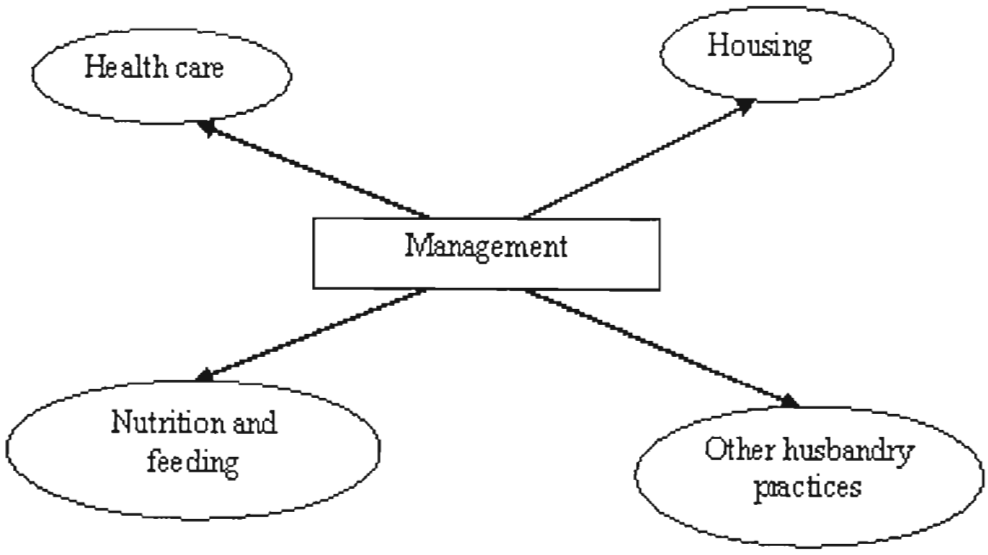

Figure 3.3: Schematic diagram of components of management practices that result in variability

Animal health management

There is a high variability in the way farmers manage the health of their animals. The way the farmer manages the health of his/her animals depends on the resources available, how he/she views the problem, his/her level of knowledge, the physical environment and the breed and the characteristics of the individual animal under consideration. Farmers apply different methods for the control of diseases and parasites affecting their animals. Control methods such as immunization, dipping, spraying, control grazing, burning of grazing land are performed differently by farmers depending mainly on the prevailing socioeconomic factors. Farmers' response to disease control programmes vary greatly. For example, some farmers do not immunize their animals due to cultural beliefs. Farmers often use different treatment methods for a given disease and in most cases even the same drug may be administered differently. The above differences in animal health management result in very high variability in on-farm trials. This variability occurs both between and within farms.

Nutrition and feeding

Nutrition and feeding are regarded as important factors affecting livestock productivity (KARI, 1994). In developing countries high variability is expected to exist in nutrition and feeding of animals between regions, seasons, farms and even within farms. This variation results from differences in quality and quantity of feed, and the method of feeding and watering. The quantity and quality of fodders, forages and other feedstuffs used for feeding livestock vary from one farm to another and from one region to another reflecting both the prevailing farming system, agro-ecological zones and marketing opportunities for products as well as the farmer's ability to purchase. In Uganda there are a lot of variations in method of feeding animals. Some farmers practice confinement feeding regime (e.g. zero grazing, intensive poultry system) while others allow their animals to wonder around (e.g. free range system in poultry). Variation also exists in the supply, source and availability of water to the animals. All the above differences contribute to variability in on-farm

trials.

Housing of animals

Housing of animals is another source of variability in management especially in the developing countries. Variation exists in the type of housing provided to animals, housing material, environmental condition (microclimate) inside the house, facilities provided and the spaces available to the animals. Most small scale farmers in developing countries like Uganda never provide sufficient shelter for their livestock especially cattle which are always kept in an open kraal. Differences in housing of animals on the farms can result in variation in animal responses.

Other animal husbandry practices

Other animal husbandry practices that contribute to variation in management include breeding methods, dehorning in goats and sheep, tail docking in pigs, debeaking in chicken, etc . Farmers use different methods of breeding such as artificial insemination and natural mating. In case of natural mating, some farmers may control breeding by castrating most males leaving only those with desired characteristics. Breeding methods used will vary from farm to farm and region to region due to socioeconomic factors such as ability of the farmer to afford the method and level of knowledge of the farmer.

3.4 Indicator variables related to the sources of variability in on-farm trials

In order to analyze the variability that exist in on-farm trials, appropriate indicator variables for the different sources of variability discussed in the previous sections need to be established. These indicator variables can either be used at the planning stages of the trial or during the analysis of the trials. For a given source of variability (management, biophysical etc), we need to specify the variable(s) that can be used as it's indicator variables (see Tables 3.1 and 3.2).

In case of uncertainties, a number of variables can be measured and the statistical

Table 3.1: Biophysical attributes

Characteristic	Possible indicator variables
Soil related characteristics	Fertility status, soil textural class, (e.g. sandy Vs loam), water retention capacity, etc
Vegetation related characteristic	Dominant species, species diversity species diversity degree, shadiness, etc
Pest and disease related characteristics	Types, range and abundance of pests, incidence, occurrence and prevalence of disease, sources of disease of pest(presence of other host), weed infestation, etc
Climate related characteristics	Rainfall (amount, availability and distribution, pattern), temperature (maximum, minimum and mean), humidity, solar radiation, etc
Topography related characteristics	Slope steepness, aspect, altitude terrain etc
Size and other characteristics of the field	Field size, distance from home to the field, distance from other field

Table 3.2: Sources of variability in animal on-farm trials and possible indicator variables

Sources of Variability	Possible indicator variables
Climate	Rainfall (amount, distribution, intensity, etc) temperatures, humidity, solar radiation
Physical environment	Topography, vegetation (type, dominance, shadiness, etc), soil characteristics
Managerial environment	
Feed and nutrition	Quality, quantity and types of feeds, water supply, feeding regime and method, supplementation, etc
Health care	Methods used for control of diseases and parasites (Immunization, deworming, dipping spraying, drug administration), frequency of application of each control method and efficiency of carrying out each method
Housing of animals	Housing material, microclimate (ventilation, humidity, temperature), spaces available to the animals, facilities (bedding, waterers, feeding troughs, etc)
Genetics Variability	
Breeds	Different breeds available
Individual animal characteristics	Age, sex, body condition, size, weight, shape

methodologies used to help us choose variables which are of importance in a particular trial. Researchers' knowledge is also of great importance in choosing appropriate variables to be used as indicators in on-farm trials. The different sources of variability may affect part of or whole of the farm. For example, some may affect only the experimental plots whereas others may affect the whole farm. We need to determine what is affected by each source of variability. This is especially important in multilevel on-farm trials.

In multilevel on-farm trials, variability occurs at each of the different levels. We need to explain the variability at those levels. Each of the levels can be treated as an investigational or sampling unit. The main task is therefore to identify the sources of variability at play in each level and the attributes or characteristics which can be associated with the different sources of variability. These attributes can be measured or recorded and used to help explain variability at each level.

In agronomic trials, variation exists between plots within a farm, between farms in a village and between villages. In a case like Uganda where the country is divided into agro-ecological zones, variability exist between plots within a farm, between farm within a village, betweens villages within a county or villages within district and between district within an agro-ecological zone (Figure 3.4). Thus we have variation at plot, farm, village, county/district and agro-ecological zone levels.

Any of the components of the four main sources of variability can be used as attribute at one or more of the levels (i.e. the attribute can be management practices, environment characteristics or socioeconomic factors). For example, village to village differences can be attributed to rainfall or temperature differences while farm to farm differences can be due to soil types, household income or management practices. Plots to plot differences may be due to treatment effects, unequal pest attacks, etc . In this way each level has one or more attributes that can help in explaining the variation that occurs in the final response. For possible biophysical attributes (indicator variables) that can be used to characterize levels of variability in on-farm trials see Table 3.1.

The following socioeconomic characteristics can be used as attributes to characterize

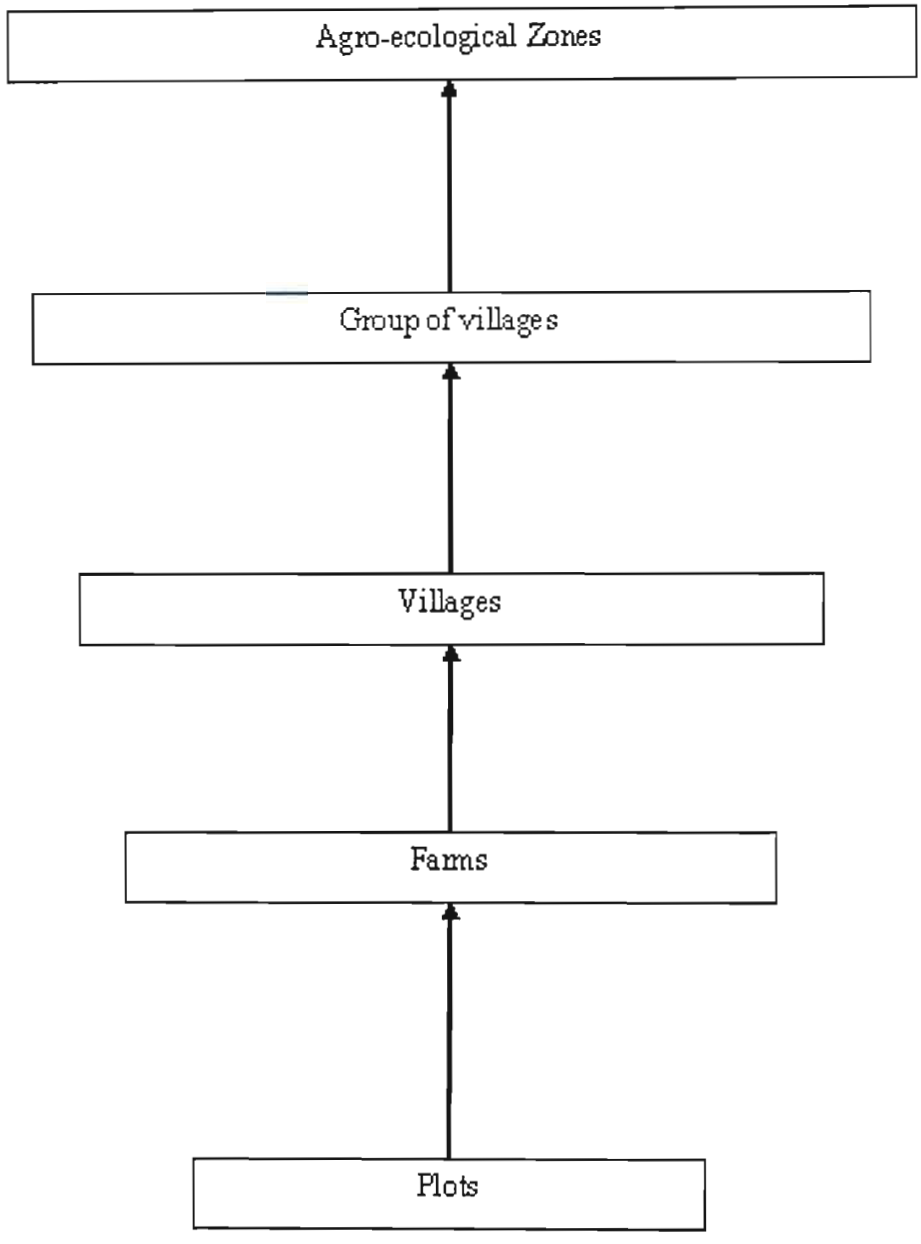

Figure 3.4: Schematic diagram of levels of variability in an agronomic on-farm trials

levels at which variability occur in on-farm trials: sex, age, occupation and educational status of the farmer, his/her family size and health status, labor availability, access to cash, agricultural input, availability of social services such as hospitals, transport, market, etc. The possible indicator variables for management practices that can be used to characterize levels at which variation occurs in on-farm trials include dates of planting, depth of planting, spacing (plant population), weeding (frequency, quality, timing, and date of weeding). Management practices can vary at all levels e.g. at plot within a farm and at farm within village (location) levels.

Animal on-farm trials have the similar levels at which variability occurs as agronomic trials. Variation can occur between individual animals within a unit (management unit, e.g. herd or pens or house), between units within a farm and between farms within a given village/location as well as between different village/locations (see Figure 3.5).

Any of the components of the two main sources of variability in animal on-farm trial can be used as attribute at one or more of the levels as in the case of agronomic trial described earlier. For the various sources of variability in animal on-farm trials and possible indicator variables that can be measured or recorded to represent the various forms of variability were given in Table 3.2. Socioeconomic factors can also be used to characterize levels at which variability occurs in animal on-farm trials in the same way they are used in agronomic on-farm trials.

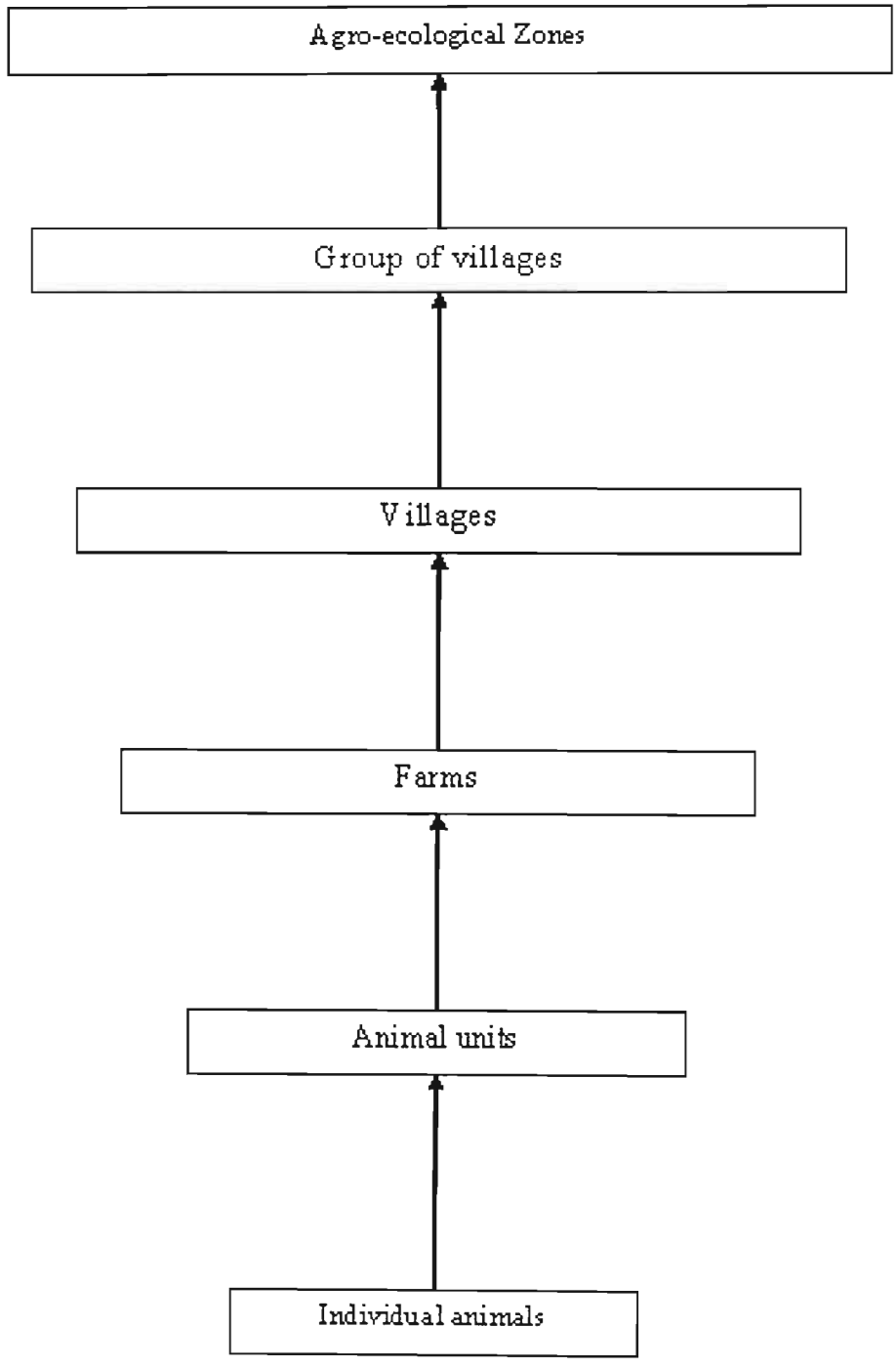

Figure 3.5: Schematic diagram of levels of variability in an animal on-farm trials

Guides on utilization of indictor variables and handling of responses

The indicator variables measured at the various levels can be used to explain variability in many ways. The quantitative or qualitative nature of these variables dictate how they can be used in the analysis of data from on-farm trials. Table 3.3 suggest how indicator variables can be utilized in the analysis of on-farm trials. The method to be used to analyze a given on-farm trial data depend on the nature of indicator variables as well as the response variables measured. Figure 3.6 give a general guide on possible methods of analysis of trial data based on scale of measurement of the response variables

Table 3.3: Utilisation of indicator variables in analysis of on-farm trials

Nature of variable	Application
Quantitative	1. Covariate in ANOVA and Mixed model 2. Explanatory variable in linear and generalised linear models (multiple regression, logistics or probit, Poisson models, etc) 3. Variables in multivariate techniques 4. Characterise environment in adaptability analysis and additive main effect and multiplicative interaction (AMMI) models
Qualitative	1. Dummy variables in linear and generalised linear models 2. Factors in ANOVA and mixed models 3. Characterise environment in adaptability analysis, AMMI models, variables in multivariate techniques

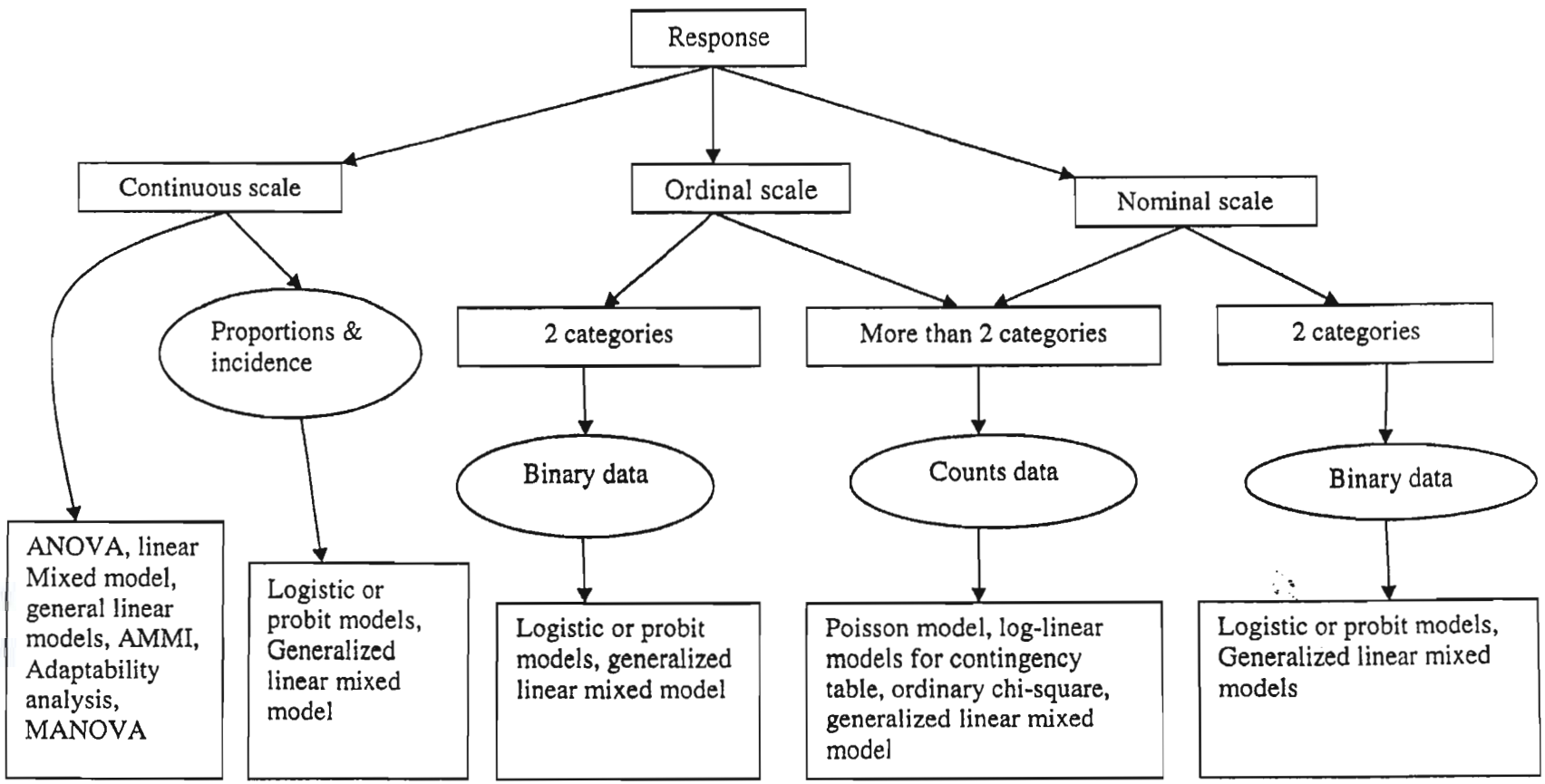

Figure 3.6: Possible methods of analysis of responses from on-farm trials

3.5 Conclusion

Variability in on-farm trials arise from many sources both experimental (treatments) and non-experimental. For proper design and analysis of on-farm trials, there is need to understand all the possible sources of variability and their likely influence on the results of the trials. Of great concern are the non-experimental sources of variability which are biophysical or socioeconomic. In farmer managed trials, management is one of the main sources of variability in both agronomic and animal trials. Each source can have an influence over a small area e.g. a plot or animal or over a wide area for example a whole farm, village or agro-ecological zone. For any source of variability to be utilized in the design or analysis of on-farm trial, we need a means of measuring it. One or more variables can be measured or recorded and used as an indicator(s) of that source. The indictor variables can be used in explaining the differences in responses from the farms.

Chapter 4

Analysis of Variability in On-farm trials

Analysis of variability is a very important part of on-farm trials. Unlike in on-station experiments where non-experimental variability is highly controlled, in on-farm trials the main aim is to explain rather than control variation. Analysis of on-farm trial data therefore involve both understanding of the different treatments/technologies and the varying farm environments. In order to be in a position to fully explain variability in on-farm trials, there is need to quantify the amount of variation that exist at the different levels in the trials. Understanding the different methods of quantifying/analysing variability can lead to a better understanding of on-farm trial results. The different methods of analysis and other statistical tools for on-farm trials are discussed in this chapter.

4.1 Approaches of analysis of on-farm variability

An understanding of the different sources of variability and the nature and extent of measurement of variability is of fundamental importance. Application of this understanding range from answering questions about experimental designs, such as how many replicates or animals are needed to achieve a certain level of precision, at what level should we replicate in the case of nested experiment, or what combination of blocking factors makes best use of the experimental resources, to the estimation of standard errors of complex surveys and the design of multi-stage selection or breeding programmes, particularly to estimate genetic gains (Robinson, 1987). In on-farm trials determination of the variance

components can help us to determine assignable causes of the observed variability.

There are two main approaches to the analysis of variability. These are the traditional analysis of variance (using the fixed effects linear models) and the mixed linear model approach. The traditional analysis of variance approach uses the method of moments to estimate the factor effects whereas the mixed linear model approach uses, among other estimation methods, the maximum likelihood (ML) and/or the restricted maximum likelihood (REML) methods.

4.1.1 The traditional analysis of variance approach (ANOVA)

Analysis of variance is generally regarded as the best method of quantifying variability (Horgan and Hunter, 1993). The resulting estimators of variance components are always unbiased, although they can yield negative estimates. The estimators are also minimum variance quadratic unbiased.

The ANOVA method of estimating variance components is to equate expected sums of square to the corresponding calculated values, the solution for the variance components are taken as the ANOVA estimates. Searle *et al.*(1992, chapter 4) has extensive details for the balanced data case. For unbalanced data (characteristics of most on-farm trials), the utility of ANOVA is severely limited. This is because with many cases of unbalanced data, there is more than one set of sums of squares that might be laid out as an analysis of variance. In such cases there are no unique estimators of variance components. An extension of this is to use not just sums of squares but the quadratic form of the data. There are also methods of the 1970's such as LaMotte's various quadratic estimators, some of which utilize a priori values of the variance components. Searle *et al.*(1992 section 11.3) discuss these methods in some detail and give extensive references. From a theoretical statistics perspective, in unbalanced data ANOVA estimators are not always based on sufficient statistics; and minimum, complete, sufficient statistics do not exist (McCulloch and Searle, 2001 p 173). As a result there is no uniform optimal ANOVA estimators.

The following are some of the practical reasons which make the traditional ANOVA approach unsuitable for analysis of variability in on-farm trials:

- There is high possibility of having data with correlated structures in on-farm trials.
- Most often heterogeneity of variance occurs in on-farm trials especially for trials with multiple levels
- On-farm trials are characterized by unbalanced/non-orthogonal designs and missing observations
- Factors involved in on-farm trials are both fixed and random.

The traditional analysis of variance approach assumes that all factor effects are fixed and this sometimes leads to underestimation of the mean treatment error term. The suitability of the ANOVA method in on-farm trial is restricted to balanced experiments with few missing observations. The multi-level nature of data from on-farm trials puts a severe limitation in the application of this approach to analyzing variability from such trials and thus the mixed model would be more suitable.

4.1.2 Mixed Model Approach

A mixed linear model is a linear model that contains both fixed and random effects. A factor is said to be fixed if the levels in the study represent all the possible levels of the factor, or at least all levels about which inferences are to be made while on the other hand factor effects are random if the factor levels that are used in the study represent only a random sample of a larger set of potential levels. We can use linear mixed model or generalized linear mixed model in analysis of on-farm trials.

The linear mixed model can be written for a vector of observations y as:

$$y = X\beta + Zu + \epsilon \tag{4.1}$$

where y is an N x 1 vector of observations, β is p x 1 vector of unknown parameters, (β is the vector of the fixed effects), X is an N x p design matrix of full rank corresponding to β ($p < N$), Z is an N x m design matrix associated with random effects, u is a m x 1 vector of random effects. A key model assumption is that u and ϵ are normally distributed with

$$E\begin{bmatrix} u \\ \epsilon \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$var\begin{bmatrix} u \\ \epsilon \end{bmatrix} = \begin{bmatrix} G & 0 \\ 0 & R \end{bmatrix}$$

G contains variance components along its diagonal and $R = \sigma^2 I$ where I denotes n x n identity matrix. Hence y has a multivariate normal distribution with means and variance $E(y) = X\beta$ and var $(y) = V = ZGZ' + R$, respectively (Corbel and Searle, 1976; Kackar and Harville, 1984 and Littell *et al.*, 1996). It can be seen that the fixed and the random effects models are special cases of the mixed effects model. In the former $u = 0$ while in the latter $\beta = 0$.

In case the response variables are not normally distributed, for example counts, binary data or proportions (binomial and poisson distributed variables), we use the generalized linear mixed model. As in the linear mixed model, a generalized linear mixed model includes fixed effect vector β, random effects vector $u \sim N(0, G)$, design matrices X and Z, and a vector of observations y whose conditional distribution given the random effects has mean μ and covariance R. In addition, a generalized linear mixed model includes a linear predictor η, and a link and/or inverse link function. The conditional mean of y, μ depends on the linear predictor through an inverse link function $h(\eta)$ and covariance matrix R depends on the conditional mean μ through a variance function. It is an extension of generalized linear model by appending Zu to the generalized linear model (McCulloch and Searle, 2001 p221). As in the linear mixed model the fixed and random are combined to form a linear predictor

$$\eta = X\beta + Zu \tag{4.2}$$

The inverse link function is used to map the value of the linear predictor for the observation i to the conditional mean for the observation i. For the linear mixed model, the inverse link function is the identity function. In this thesis we concentrated our effort on linear mixed model (generalized linear mixed models is considered as it's modification).

Why mixed model is suitable for on-farm trials

In on-farm trials new technologies are tested in the farmers' fields under their own conditions. Because we cannot use all the farms for the trial, a sample is selected from which inferences are to be made about the entire population of farms in the area under consideration. In this case since the farms used in the study are a random sample from population of farms, the farm effect is therefore considered random. The treatments/technologies under investigation constitute the fixed effects in the model (if those are only one we are interested in). Since on-farm trials have both fixed and random factors, a mixed model is appropriate for such trials.

There is a great deal of imbalance in the data from on-farm trials. Many authors argue against having many treatments in a farmer's field implying that in case the researcher is interested in testing all his/her treatments then he/she may have to resort to incomplete block designs which in most cases are unbalanced. Incidence of missing data is also very frequent in on-farm trials often making even a balanced experiment to become unbalanced. All this makes the use of traditional analysis of variance less appealing and thus mixed model approach becomes a better alternative under such circumstances. Other attributes of on-farm trials that make mixed models suitable for use are possibilities of having both heterogeneity of variance and correlated observations. The variances at the different levels are rarely constant, and most often observations in on-farm trials are highly correlated depending on the experimental setup. For example, observations from farms from the same village are more correlated compared to those from other villages.

Illustrative models

The primary objective of conducting on-farm trials is to address farmers production problems. For instance, in Uganda most on-farm trials are designed in such a way that the needs of the farmers in different parts of the country are met. Conducting on-farm trials over a wide area requires consideration of the farm types and regions where they are located. Within the African context, villages are composed of farms, and the villages may

cut across agro-ecological zones. Involvement of farmers in the trials requires selection of representative samples of either the farms or the villages. The nesting of farms within the villages, villages within agro-ecological zones, etc., suggests for the use of the multi-level approach in handling on-farm trials. Consideration of the auxiliary information collected in farm surveys need to be made when analyzing actual on-farm trials data which is mainly biophysical. In recognition of the fact that on-farm trials are multi-level in nature, mixed models for agronomic and animal on-farm trials are considered below.

Agronomic on-farm trials

The nature of the response of an agronomic trial takes different forms depending on the interest of the study. The general model likely to be adopted is of the form:

$$y_{ijklm} = \mu + \alpha_i + v(\alpha)_{ij} + f(v)_{jk} + \delta_l + \alpha\delta_{il} + \delta v(\alpha)_{ijl} + \delta f(v)_{jkl} + \epsilon_{ijklm} \qquad (4.3)$$

$i = 1, 2, ..., a;\quad j = 1, 2, ..., v;\quad k = 1, 2, ..., f;\quad l = 1, 2, ..., t;\ m = 1, 2, ..., b.$

Where y_{ijklm} is the observation from the mth replicate of the lth treatment from the kth farm in the jth village in the ith agro-ecological zone, α_i is the effect of the ith agro-ecological zone, $v(\alpha)_{ij}$ is the effect of the jth village nested in the ith agro-ecological zone, $f(v)_{jk}$ is the effect of the kth farm nested in the jth village, δ_l is the effect of lth treatment, $\alpha\delta_{il}$ is the (il)th interaction between the ith agro-ecological zone and the lth treatment, $\delta v(\alpha)_{ijl}$ is the (jl)th interaction between the lth treatment effect and the jth village nested within the ith agro-ecological zone, $\delta f(v)_{jkl}$ is the (lk)th interaction between the lth treatment and the kth farm nested in the jth village and ϵ_{ijklm} is the random error term. The effects $v(\alpha)_{ij}$, $f(v)_{jk}$, $\delta v(\alpha)_{ijl}$, $\delta f(v)_{jkl}$ and ϵ_{ijklm} are assumed to be *iid* normal with means 0 and variance components $\sigma^2_{v(\alpha)}$, $\sigma^2_{f(v)}$, $\sigma^2_{\delta v(\alpha)}$, $\sigma^2_{\delta f(v)}$ and σ^2, respectively. The effects of the agro-ecological zones and the treatment are assumed to be fixed. In this case we have 4 levels at which variability can occur:

At level 1 we have plots within farms;

At level 2 we have farms within villages;

At level 3 we have villages within agro-ecological zones;

At level 4 we have agro-ecological zones.

Animal on-farm trial

The general model likely to be adopted for animal on-farm trial is of the form:

$$y_{ijklmn} = \mu+\alpha_i+v(\alpha)_{ij}+f(v)_{jk}+u(f)_{kl}+\delta_m+\alpha\delta_{im}+\delta v(\alpha)_{ijm}+\delta f(v)_{jkm}+\delta u(f)_{lm}+\epsilon_{ijklmn} \quad (4.4)$$

$i = 1, 2, ..., a;\quad j = 1, 2, ...,v;\quad k= 1, 2, ..., f;\quad l = 1, 2, ..., t;\ m = 1, 2, ..., b;\ n = 1, 2, ..., N.$

Where y_{ijklm} is the observation from the nth animal receiving the mth treatment in the lth unit (unit used as defined in Section 3.4) on the kth farm in the jth village in the ith agro-ecological zone, α_i is the effect of the ith agro-ecological zone, $v(\alpha)_{ij}$ is the effect of the jth village nested in the ith agro-ecological zone, $f(v)_{jk}$ is the effect of the kth farm nested in the jth village, $u(f)_{kl}$ is the effect of the l unit nested in the kth farm, δ_m is the effect of mth treatment, $\alpha\delta_{im}$ is the (im)th interaction between the ith agro-ecological zone and the mth treatment, $\delta v(\alpha)_{ijm}$ is the (jm)th interaction between the mth treatment and the jth village nested within the ith agro-ecological zone, $\delta f(v)_{jkm}$ is the (km)th interaction between the mth treatment and the kth farm nested in the jth village, $\delta u(f)_{lmk}$ is the (lm)th interaction between the mth treatment and lth unit in the kth farm and ϵ_{ijklmn} is the random error term. The effects $v(\alpha)_{ij}$, $f(v)_{jk}$, $\delta v(\alpha)_{jk}$, $\delta f(v)_{jkm}$, $u(f)_{kl}$, $\delta u(f)_{lm}$ and ϵ_{ijklm} are assumed to be iid normal with means 0 and variance components $\sigma^2_{v(\alpha)}$, $\sigma^2_{f(v)}$, $\sigma^2_{\delta v(\alpha)}$, $\sigma^2_{\delta f(v)}$, $\sigma^2_{u(f)}$, $\sigma^2_{\delta u}$ and σ^2, respectively. The effects of the agro-ecological zones and treatment are assumed to be fixed. In this case we have five (5) levels at which variability occurs:

At level 1 we have animals within animal units;

At level 2 we have animal units within farms;

At level 3 we have farms within villages;

At level 4 we have villages within agro-ecological zones;

At level 5 we have agro-ecological zones.

Possible setup of on-farm trials and suggested on-farm models

The agronomic trial model will be used for illustration purposes.

Setup 1

Consider a simple agronomic on-farm trial model with two levels at which variability occurs (farm and plot) no replication within a farm as is always the case in most trials for reasons cited in section 2.4:

$$y_{ij} = \mu + \tau_i + f_j + f\tau_{ij} \tag{4.5}$$

$i = 1, .., t; \quad j = 1, ..., f;$

where y_{ij} is an observation from the ith treatment in the jth farm, μ is the overall mean, f_j is the jth farm effect, τ_i is the ith treatment effect and $f\tau_{ij}$ is the effect of the (ij)th interaction between treatment i and farm j with $f_i \sim iidN(0, \sigma_f^2)$, $f\tau_{ij} \sim iidN(0, \sigma_{f\tau}^2)$. The model assumes constant variance and zero correlation among random effects. Thus equation (4.5) can be written in the form of equation (4.1):

$$y = X\beta + Zu + \epsilon \tag{4.6}$$

where:

$X\beta = 1'\mu + X_t\tau$, or $X = (1' \; X_t)$, $\beta = (\mu \quad \tau)'$;

$Zu = Z_f f + Z_{f\tau} f\tau$ or $Z = (Z_f \; Z_{f\tau})$ $u = (f \; f\tau)'$.

In this case the variance components to be estimated are σ_f^2 and $\sigma_{f\tau}^2$. Between farm variability is measured by the value of σ_f^2 whereas $\sigma_{f\tau}^2$ measures the combined interaction and unexplained within farm variability. The estimate of $\sigma_{f\tau}^2$ is used as the error term in testing the significance of the fixed effects since lack of replication implies that the pure experimental error is not estimable.

Setup 2

Under some circumstances a researcher may be interested in replicating treatments within the farms. In this case the number of levels at which variability occurs increases from two in the above to three, the new level being block within farm. The model for an on-farm trial where we have replications within a farm is:

$$y_{ijk} = \mu + \tau_i + f_j + b(f)_{jk} + f\tau_{ij} + \epsilon_{ijk} \tag{4.7}$$

$i = 1, 2, ..., t;\ \ j = 1, 2, ..., f;\ \ k = 1, 2, ..., r;$

where y_{ijk} is an observation of the kth replicate of the ith treatment in the jth farm, μ is overall mean, f_j is the jth farm effect and τ_i is the ith treatment effect, $b(f)_{jk}$ is the effect of the kth block nested in the jth farm, $f\tau_{ij}$ is the farm-by-treatment interaction effects ϵ_{ijk} is the error term. The random effects f_j, $f\tau_{ij}$, $b(f)_{jk}$ and ϵ_{ijk} are assumed to be *iid* normal with means 0 and variances σ_f^2, $\sigma_{f\tau}^2$, σ_b^2 and σ^2, respectively.

Equation (4.7) can be written in the form of equation (4.1) where

$X\beta = 1'\mu + X_t\tau$ or $X = (1' \ \ X_t),\ \beta = (\mu\ \tau)'$;

$Zu = Z_f f + Z_b b + Z_{f\tau} f\tau$ or $Z = (Z_f \ \ Z_b \ \ Z_{f\tau});\ u = (f\ \ b\ \ f\tau)'$.

Here the variance components to be estimated are σ^2, σ_f^2, σ_b^2, $\sigma_{f\tau}^2$ with σ^2 measuring the variability between plots within farm, σ_f^2 measures the variability between farms, σ_b^2 measures variability between blocks within farm and $\sigma_{f\tau}^2$ measures variation due to interaction between treatment and environment represented by farms.

In case farm effects are considered as fixed effects, i.e. when the specific farms are of interest, then all the above models become fixed effects models.

Setup 3

In both models (4.5) and (4.7), we assume that the farms do not share many characteristics in common. However, since other sources of variation have influence over a wide area, this implies that a number of farms may share similar characteristics thus can be put in

one group. They could share biophysical or socio-economic characteristics. The group effects can be treated as fixed or random. This tantamount to including another level in the hierarchy. The groups can for example be villages or locations or agro-ecological zones, etc. The farms in this case will be nested within the groups.

The models for trials where farms are in groups, which share similar characteristics

(i) When there are replicates within the farm and the group effects are considered as fixed effects (assume these are the only groups we want to draw inference on. For example groups can be based on agro-ecological zones of the farms) the model is:

$$y_{ijkl} = \mu + \tau_i + b(f)_{jk} + f(\rho)_{jl} + \rho_l + f\tau_{ij} + \rho\tau_{il} + \epsilon_{ijkl} \tag{4.8}$$

(ii) When there are replicates within farm and the group effects are considered random (farms from the different villages can constitute groups whose effects can be assumed to be random) the model is:

$$y_{ijkl} = \mu + \tau_i + b(f)_{jk} + f(g)_{jl} + g_l + f\tau_{ij} + g\tau_{il} + \epsilon_{ijkl} \tag{4.9}$$

In both (4.8) and (4.9), $i = 1, 2, ..., t$; $j = 1, 2, ..., f$; $l = 1, 2, ..., m$; $k = 1, 2,..., r$. Furthermore y_{ijkl} is an observation of the kth replicate of the ith treatment in the jth farm belonging to the lth group, μ is overall mean, τ_i is the ith treatment effect, $b(f)_{jk}$ is the effect of the kth replicate within the jth farm, g_l is the lth group effect(random), ρ_l is the lth group effect (fixed) and $f\tau_{ij}$ is the farm-by-treatment interaction effect, $\rho\tau_{il}$ and $g\tau_{il}$ are group-by-treatment interaction effects and ϵ_{ijkl} is the error term. In models (4.8 and 4.9) the random effects, $f(\rho)_{jl}$, $f(g)_{jl}$ $b(f)_{jk}$, $f\tau_{ij}$, g_l, $g\tau_{i(l)}$ and ϵ_{ijkl} are assumed *iid* normal with means 0 and variance components $\sigma^2_{f(\rho)}$ $\sigma^2_{f(g)}$, $\sigma^2_{b(f)}$, $\sigma^2_{f\tau}$, σ^2_g, $\sigma^2_{g\tau}$ and σ^2, respectively. These are the variance components to be estimated.

Equation (4.8 and 4.9) can also be written in the form of equation (4.1).

Estimation procedure for a linear mixed model

For estimation of variance components in a linear mixed model, the method of maximum likelihood (ML) and the restricted maximum likelihood (REML) methods are used among

others. The description and illustration of ML and REML procedures is available in several textbooks, journals and theses (Hartely and Rao, 1967; Patterson and Thompson, 1971; Harville, 1977; Robinson 1987; Kackar and Harville, 1988; Levin, 1999; McCulloch and Searle, 2001).

Model selection in mixed model analysis

In mixed model, two distinct test of hypotheses (i.e. fixed and random effects)need to be done. The likelihood ratio test like the one described for standard linear models can be used to test hypotheses about random effects, i.e. we can examine the change in the log-likelihood due to adding one or more random effects in the model, and compare this change to the percentage points of a chi-squared distribution with q^* degrees of freedom, where q^* is the number of additional dispersal parameters (such as components of variance) added to the model (Levin, 1999).

The REML procedure in Genstat gives the model deviance (for theory on model deviance see Dobson, 1990), and thus tests on the random effects can be carried out by fitting models with the same fixed effects, but having different random effects.

A number of model fitting information (goodness of fit statistics) are provided by SAS PROC MIXED (SAS 1996, 1999) and these include model deviance (-2 loglikelihood), Akaike's Information Criterion (AIC), Schwarz's Bayesian Criterion (SBC) and the 'Null model LRT chi-square' statistic. All these can be used in deciding on the random effects to be included in the model, and for each of them the larger the value the better the fit of the model to the data.

For testing hypotheses about fixed effects, large sample Wald tests and F-tests can be used. We consider estimable linear combinations of the form $L\beta$ (L is a matrix of contrasts), and consider testing the hypothesis:
H_0: $L\beta = 0$ against the general alternative hypothesis (H_0: $L\beta \neq 0$). The Wald statistic for testing this hypothesis is given by $(L\hat{\beta})^T(L^T(X^TV^{-1}X)^{-1}L)^{-1}(L\hat{\beta})$. Under H_0 the Wald statistic is approximately distributed as chi-squared with ν degrees of freedom, where $\nu = \text{rank}(L)$ (Littel *et al.*, 1996, Chapter 11 and Appendix 1). In the REML

procedure in Genstat the Wald statistics are calculated from the Cholesky decomposition of the matrix $Y^TV^{-1}Y$, where Y is the fixed model design matrix X augmented with the vector of responses y (Levin, 1999) . The Cholesky decomposition sequentially removes the sums of square due to each of the fixed effects in turn, ignoring all terms following later in the model (Levin 1999). Therefore the Wald statistics assess the change in fit due to adding current term to the model containing all the terms that precede the term under consideration. By default PROC MIXED in SAS uses a Type III statistics for testing the significance of the fixed effects. It computes the test statistics by first constructing a Type III statistic matrix **L** for each treatment effect. This **L** is then used to compute the following **F**-statistic:

$$F = \frac{\hat{\beta}' L' [L(X'\hat{V}^{-1}X)^{-}L']^{-}L\hat{\beta}}{rank(L)} \tag{4.10}$$

A p-value for the test is computed as the tail area beyond this statistic on an F-distribution with numerator degrees of freedom (NDF) and denominator degree of freedom (DDF). The NDF is the row rank of **L**, the DDF is computed using methods such as Satterthwaite (1946) or else using 'method of containment' (SAS PROC MIXED) (SAS, 1996, 1999). The method to be used can be specified in PROC MIXED.

The asymptotic approximation of a chi-squared distribution for the Wald statistics under the null hypothesis is reasonable when the number of degrees of freedom used to estimate the variance parameters is large. The Wald chi-square is more liberal compared to the F-test (Type III) because it effectively assumes an infinite denominator degrees of freedom.

4.2 Other statistical approaches for analysis of on-farm trials

The problems associated with design and execution of on-farm trials often make it quite hard to apply conventional methods of statistical analysis to data from such trials. As mentioned earlier (Chapter 2) on-farm trials are associated with single replication, missing observations and high variability, and thus there is need for special methods of analyzes

which take care of the above mentioned problems. For on-farm trials to meet their set objectives, there is need to establish a clear relationship between the quantified variability and the various sources of variability that exist in the trials. We need to utilize the observed variability in drawing inferences (about the treatment effects) and coming up with recommendation domain. In addition to the mixed model approach discussed in section 4.1, a number of useful statistical approaches are available and can be used to analyze these trials. Two of these approaches are discussed below.

4.2.1 Additive main effects and multiplicative interaction models (AMMI)

Traditional ANOVA test for interaction between treatments and farms when the experiment is replicated. In non-replicated experiments such as those carried out on farms, interaction effects between treatments and farms are lumped together with random errors, and the combined effects are used to test the treatment main effects (additive part of the model). Thus the analysis provides little or no insight into the particular pattern or structure of the treatment-by-farm interactions. Multiplicative models have been proposed as one of the ways of extracting information on treatment-by-farm interactions from such trials. According to Shaffii and Price (1998), in analyzes of genotype-environment interaction, the additive main effects and multiplicative interaction model (AMMI) incorporates both additive and multiplicative components of a two-way data structure which can explain effectively the underlying interaction patterns.

Consider a non-replicated on-farm trial. The analysis of variance model can be given as:

$$y_{ij} = \mu + \tau_i + f_j + \epsilon_{ij} \tag{4.11}$$

where y_{ij} is observation from the ith treatment in the jth farm, μ is overall mean, τ_i is the additive main effect of the ith treatment, f_j is the additive main effect of the jth farm and ϵ_{ij} is the residual effect. The residual is decomposed into multiplicative terms which equal the interaction between the treatments and farms plus the error terms. The additive main effect and multiplicative interaction model represents an observation as

consisting of a systematic component that includes the main effect as well as one or more multiplicative interaction terms, besides a random component for residual variation or 'error' (Eeuwijk, 1995).

The use of AMMI has in the recent years been mainly in plant breeding for modelling the genotype-by-environment interaction in a two-way table. Some authors have suggested that the model can also be used to model treatment-by-farm (location) interaction in on-farm trials (Nokoe, 1999; Oyejola, 1999). In this case genotype is replaced by the technology (treatment) being tested and the farms replace the environment. Nokoe (per. comm.) suggested that instead of using individual farm/field as an environment, farms/fields can be put in groups with similar characteristics to represent the different environments (the farms/fields within each group are used as replicates).

To apply AMMI, the main effects are first estimated using the standard additive (i.e. no interaction) ANOVA model. Principal Component analysis is then applied to the interaction (residual) portion from the additive ANOVA model to extract a new set of coordinate axes which account more effectively for the interaction pattern (Shaffii and Price, 1998). Statistical computations and estimation of AMMI can be performed by, among others, PROC GLM and PROC IML of SAS (SAS 1996) and Genstat Release 6.1 (2000) has incorporated direct method of analysis using AMMI.

Visual display of interaction by means of biplot

The biplot technique (Gabriel, 1971), provides a graphical representation of the pattern of interaction which allows each treatment in each farm/environment predicted by the multiplicative models to be directly identified. Regularities in the pattern of response and individual outliers are quickly identified by the method which thus provides a useful initial exploratory analysis prior to setting up formal hypotheses. Biplot constitute a powerful tool for displaying interaction, which is described by the multiplicative terms in an AMMI model (Gabriel, 1971; Kempton, 1984). From a given data set a number of plots can be made and this include Finlay-Wilkison plot of mean yields (Finlay and Wilkison, 1963)and sensitivity coefficient and plot of principle components. If a set of

adjusted yields for variety/treatment j,

$$Y^*_{ji} = Y_{ji} - Y_{.j} - Y_{i.} + Y_{..}$$

$$(i = 1, ...n)$$

is represented as a point in n-dimensional space then the first principal component is obtained as that axis drawn through the space which maximizes variation between treatments. The second principal component is that axis, at right angles to the first, which maximizes the remaining variation, and so on(Kempton, 1984). When the majority of the variation in treatment responses is accounted for by the first two principal components, a plot of treatments on these two axes provides a succinic description of the data.

According to Kempton, (1984) an alternative and possibly more instructive derivation of principal component plots for displaying treatment-environment interactions identifies the distances between a pairs of treatments in the n-dimensional space with their interaction over environments. The interaction sums of square for treatment j and j' over the n environments is

$I_{jj'} = \frac{1}{2}\sum_i (Y^*_{ij} - Y^*_{ij'})^2$,

and the total treatment-environment interaction sum of squares may be expressed as a sum of $I_{jj'}$ for all pairs of treatments j and j',

$\sum_j \sum_i Y^*_{ij} = 2\sum_j \sum_{j'<j} \frac{I_{ij}}{n}$.

Now $d_{jj'} = 2I_{jj'}$ is the squared Euclidean distance between two points j and j' in the n-dimensional space. Thus pairs of treatments for which $d_{jj'}$ is small will have small joint interaction sum of squares and show similar pattern of response over the environments, although possibly differing overall mean yield. The principal components technique now displays the treatments in a small number of dimension (usually two or three) so that the graphical distances between all pairs of treatments j and j' is as close as possible to the

actual squared Euclidean distances $d_{jj'}$. Milliken and Johnson (1989) gave a detail look at AMMI modelling.

Suitability of AMMI for on-farm trial

The ability of AMMI to effectively handle both replicated and un-replicated experiments makes it a suitable tool for use in on-farm trials where non-replicated experiments are very common. Gauch, (1990) found AMMI useful for understanding complex interactions, gaining accuracy and increasing experimental efficiency. Whenever interactions exist, the multiplicative part of the model can enable us to detect which treatments are interacting with the farms and which ones are not. The result can be graphed in a very informative biplot that show both main effects and interactions for both treatments and farms. The plots can also enable us to group farms according to similar environment. Besides indicating farm differences, the use of AMMI can also contribute to identification of major environmental variables and treatment factors related to the interaction between farm and treatment. Additive main effect and multiplicative interaction modelling is a very useful tool for interpreting association between environmental variables and components of treatment-by-farm interaction. This is done by correlating AMMI parameters with environmental data. This can allow a researcher to come up with recommendation domain for the technology under consideration.

The greatest weakness of AMMI modelling is that it considers farm effect as being fixed. Many authors have also argued that biologically it is very complicated to explain the multiplicative part of AMMI models. AMMI modelling is requires data to be in a two-way table layout and this necessitates that the data be converted into a two-way table format before analysis. AMMI modelling is appropriate for quantitative data with normally distributed errors. However a generalized version of AMMI, (GAMMI) has been developed to accommodate other error structures(see Eeuwijk, 1995). The natural application of GAMMI has been to disease incidences on plants, which frequently have non normal error distribution.

4.2.2 Adaptability Analysis (AA)

Adaptability Analysis (AA) also described as modified stability analysis(MSA) aim at partitioning farms into more homogenous groups for the purposes of making recommendations for each group. These homogenous groups are called recommendation domains (Byerlee, Collinson *et al.*, 1980). Adaptability analysis incorporates variation in farm management as well as soils and climate, to help the agronomist evaluate responses to technologies/ treatments, and partitions farms into recommendation domains (Hildebrand, 1984). In the case of farmer managed trial AA is mainly used to study the response of different materials or technologies to both good and poor management practices. Initially this method of analysis was used for multi-location variety trials where the interest was mainly in the determination of performance of a variety over a range of environments (Eberhat and Russell, 1966). Eberhat and Russell (1966) utilized mean varietal yields at each location in a multi-location trial to define stability parameters to be used to describe the performance of a variety over a series of environments. Mackenzi *et al.*, 1976, expanded this concept by including farmer management as one of the sources of variation. Hildebrand (1984), argued that the explicit incorporation of different environments while not negating year to year variation, should reduce concern with that variation so that recommendations can be delivered to the farmers in the shortest possible time.

In AA we assume all the plots or animals in a given farm are identical, and variation between the farms is considered as the most important since they influence the treatment effects. In order to quantify this variation we need a simple indicator value which characterizes the overall conditions in a particular farm. An obvious choice is the mean performance of all experimental plots or animals in a given farm which is referred to as the environmental or site index. This index is an estimate of each environment's capacity to produce the crop or livestock product in question under the technology being tested. The site index can be used to determine how treatment effects vary with farm conditions (farm-by-treatment interaction).

For illustration, consider an on-farm trial in which the effects of three different varieties

(or new technologies) A, B, and C are being tested. If we assume that the farmers maintain their usual practices, the only constants at each farm are the three varieties under investigation. Each farmer subjects them to different soil conditions, planting dates, pest control, fertilizer and other management practices. A farm for which the average yield of the three varieties is high for whatever reasons is considered a 'good' environment for the varieties as measured by the average yield while the one for which the average yields is low is considered a 'poor' environment. Environment then becomes a continuous, quantifiable variable whose range is the range of the average yields.

In the adaptability analysis the yield of a given variety can be related to the environment by simple linear regression for each treatment as:

$$y_{ij} = \alpha_i + \beta_i x_j + \epsilon_{ij} \tag{4.12}$$

$i = 1, 2, \ldots, t;\ \ j = 1, 2, \ldots, f.$

where y_{ij} is yield of the ith variety obtained from farm j with site index x_j:

$$x_j = \frac{\sum_i y_{ij}}{t} \tag{4.13}$$

where t is the number of technology being tested (in the variety example $t = 3$).
By fitting the above equation independently for each variety and looking at the slope (regression coefficient), the adaptability of each variety can be determined.

Interpretation of regression coefficient in AA

Adaptability analysis uses regression of treatment response on environment (environmental treatment means) to identify those technologies/treatments that are best adapted to a particular environment. Following Finlay and Wilkinson (1963) and Eberhart and Russell (1966), a technology/treatment for which $\beta_i = 1$ is considered to have 'average stability' or 'well adapted to most environments'. A technology/treatment for which $\beta_i < 1$ would perform better than the average of all tested technologies (.i.e., is well adapted) in low-performing environments; those for which $\beta_i > 1$ would perform better than the average (and therefore better adapted) to high-performing environments. A treatment/technology

for which regression slope (β_i) close to 1.0 is less responsive to changing environments (i.e. has little interaction with environment). A smaller R^2 value is associated with erratic responses to the various environments and hence less stability.

A plot of performance of each treatment/technology against the environmental index makes it possible to visually compare the performance of treatments/technologies across environments and come up with recommendation domains based on whether there are interactions or not. Cross-over of lines (nonparallel lines) signify the presence of interactions of treatments with environments.

A test of the significance of the slope differences is equivalent to the test for the presence of the interactions between 'site index' and treatment in the ANOVA. The test for the significance of the slopes can be performed using most statistical packages. In Genstat statistical package the directive 'simple linear regression with group' gives the tests for site index and site index-by-treatment interactions. The environmental index can also be used in ordinary ANOVA as a quantitative factor with number of environment acting as the levels of the quantitative factor. In this case we can determine at least linear and quadratic components of interaction between the treatment and environment without replication (the higher order interaction is used as error term). This can easily be performed using most statistical packages.

According to Hildebrand and Russell, (1996 pp 30 - 31), the following steps should be followed in AA.

1. Conduct the trial according to the planned methods of analysis. The trial to be analyzed using AA should include data which adequately characterize each environment and permit calculation of relevant evaluation criteria.

2. Calculate the environmental index (EI).

3. Relate treatment response to EI through regression analysis and/or scatter plot.

4. Compare the response of treatments to EI and estimate treatment-by-environment interaction

5. If the treatment-by-environment interactions are present, relate EI to environmental characterization and divide environments into potential recommendation domains. If no clear relationship can be shown between EI and any of the environmental characteristics on which the data were collected, divide environments based on yield of 'checks' i.e. of farmers' current practices.

6. Interpret results and define recommendation domains.

Short comings of adaptability analysis (AA)

Statistically the main weakness of adaptability analysis is that the environmental index on which it is based is not independent of the treatments effects. This type of analysis violates an assumption of least-squares regression that the dependent and independent regression variables be independent of each other (error terms are correlated in this case). The main problem with this is that the estimates of β_i and other regression statistics, as well as tests of significance are biased (Hildebrand and Russell, 1996, p 24). Despite the above concerns, many authors including Freeman (1973) and Lin, Bin and Leftkovitch (1986) have maintained that until multivariate techniques using independent environmental measures are developed, linear regression on means still remains a very useful technique. It's advantages are that it is relatively simple and more importantly, that it permits an analysis of structure of interactions, i.e. a graphical representation, of the treatment-by-environment interaction.

If we are using adaptability analysis for identification of specifically adapted technologies, particular care must be given to ensure that the range of environments in a trial be representative of the range of the environments that exist over years (Hildebrand and Russell, 1996, p 33). This is sometimes hard to achieve unless enough information is available. Experience has shown that for the estimates of environment-treatment responses to be consistent across years, the followings three conditions should be met in each year's trial (Hildebrand and Russell, 1996, p 33):

1. The range of the environmental indices (EI) should be at least as large as the mean

of the index values, i.e. the ratio of the range to mean should be at least one.

2. The distribution of environmental indices (EIs) should be reasonably uniform from smallest to largest index.

3. The range and distribution of the yield/performance of farmers' current practices should approximate those normally expected over a period of years.

Dividing the range of EIs by the overall mean EI is a useful measure of the representativeness of the data. On-farm data usually have greater range than station trials. A very narrow range, resulting in ratios less than one usually indicates that the mean yields were very high and probably that the best farms were selected for the study or the trials were highly controlled.

Adaptability analysis also requires that all the treatments should appear in all site or farms. This can be of great problem since most on-farm trials are characterized by missing observations and are unbalanced in nature.

4.3 Conclusion

On-farm trials in most cases are multilevel in nature and at each level, variability from the different sources described in chapter 3 occurs. This implies that each level (e.g. plot/individual animal, farm, village or agro-ecological zone) contributes to the total variability in the observed response. It is important therefore to estimate variability associated with those levels for proper understanding of the trial result. For estimation of variability in on-farm trials mixed model approach is preferred. The distributional assumptions of the random terms in the traditional analysis of variance (linear model) is too restrictive. The assumptions of zero correlation and homogeneity of variance are most often violated in on-farm trial and these put sever limitation on application of traditional ANOVA in such trials. The applicability of traditional ANOVA in on-farm trial is restricted to balanced experiment with limited amount of missing observations. Mixed model on the other hand does not require the trial to be balanced and allows

for both correlation and heterogenous variances as part of the model. Mixed model in particular is more suitable for multilevel trials compared to the traditional ANOVA approach.

Interaction between the farms and treatment/technology can also contribute tremendously to the variability observed in the response. In conventional on-station statistical methods, this interaction can only be tested when there is replication within the farm. Additive main effect and multiplicative interaction(AMMI) model and adaptability analysis provide us with options for understanding this interaction without the need for within farm replication. Graphical representation from these two methods provides simple method understanding farm-by-treatment interaction.

Chapter 5

Case study

The bulk of agricultural production in Uganda is carried out by subsistence farmers. These resource limited farmers operate under very high production constraints. The government recognizes this fact as noted from the direction taken by agricultural research in Uganda. On-farm trial has been one of the main tools used by the national agricultural research organization to address the production constraints faced by subsistence farmers in Uganda. The problem faced by subsistence farmers and the needs for on-farm trials as a mean of finding solutions to them is common to most developing countries, and thus Uganda can be used as a case study. The efficient analysis of on-farm trials is a single most important factor that determines how the solutions to farmers' problems can be reached. Given that high variability is associated with on-farm trials, their analysis requires the efficient estimation of this variability. The main purpose of this chapter therefore, is to present and illustrate procedures introduced in Chapter 4 in handling on-farm variability in some on-farm trials carried out in Uganda. The three examples that have been taken as representatives of the on-farm trial activities taking place in Uganda are used for this purpose.

5.1 An overview of status of on-farm trials in Uganda

5.1.1 Introduction

The main aim of the overview of status of on-farm trials in Uganda is to find out how researchers are coping with problems of on-farm trials in the country. Also of interest is

the assessment of the methods used by researchers in Uganda in comparison to the general methods recommended by statisticians/biometricians for on-farm trials. The understanding of this is thought to be necessary before discussing the methods presented in Chapter 4. This overview was based on research works done by the faculty of agriculture of Makerere University Kampala (MUK), and national research institutes: Kawanda Agricultural Research Institute (KARI), Serere Agricultural and Animal Research Institute (SAARI) and Namulonge Agricultural and Animal production Research Institute (NAARI) from the period 1997 to 2001. The information presented here was extracted from samples of annual reports of national research institutes and postgraduate theses from Makerere university, most of which are unpublished. The information sought included types of on-farm trials, types of the designs used in those trials, number of farms used in each trial, number of replications within farm/site, plot sizes, number of treatments per trial and methods of analysis used in each case. Forty (40) agronomic trial reports were reviewed (15 from MUK, 10 from KARI, 10 from NAARI and 5 from SAARI). Reports from animal trials and socioeconomic studies were not readily available.

5.1.2 Types of on-farm trials

For the purpose of this study on-farm trials have been classified according to the level of participation of the farmer as far as management and decision-making is concerned. We have four categories/types:

- Researcher designed and managed where the farmer provided land and labor. The researcher makes all the decision concerning management and only instructs the farmer on how to carry out management practices.

- Researcher designed and researcher-farmer managed; here the farmer and researcher plan management activities together but the farmer is free to decide when to carry out those activities within some specified period of time.

- Researcher designed and farmer managed; in this case after setting up the experiment with the farmer, the researcher leaves all the decisions concerning the manage-

ment with the farmer. The researcher only monitors the progress of the experiment.

- Farmer designed and managed; unlike in the above three cases where the researcher designs the experiment, in this case it is the farmer who designs and manage the experiment with researcher as possibly an adviser. In most cases, the researcher's role is just to monitor and obtain information not even advisory.

From the review most trials in Uganda fall in the first category, i.e. researcher designed and managed (50% of the trials) trials (Table 5.1). This is probably due to the fact that

Table 5.1: Types of on-farm trials conducted in Uganda between 1997 - 2001

Type of on-farm trial	Frequency	Percentage
Researcher designed and managed	20	50
Researcher designed, researcher-farmer managed	11	27.5
Researcher designed, farmer managed	9	22.5
Farmer designed and farmer managed	0	0
Total	40	100

high levels of participation by farmers would introduce high variability which researchers do not feel confident enough to handle. The students, for example, have just two years to finish the master's degree programme, thus any complication in the trial would mean delay in completion of the study. Hence there is the tendency for researchers to maintain the status quo, i.e. maintain the experimental setup similar to the one on-station. Most researchers still believe that variability has to be controlled but not analyzed and explained. However the number of experiments being left entirely to be managed by farmers is increasing due to the introduction of farmers' school field where an experiment is set up in one farmer's field and it is collectively managed in a group of 10 - 20 farmers in an area. Because the study used information only from the university and research institutes, farmer designed and managed on-farm trials were not reviewed. This is because it is very rare for farmers in developing countries like Uganda to send their farming/activity records to be documented either by the university or the research institutes. It is hoped that with increased interest in farmers' school field experimentation even farmer designed and managed trials will be taken up in the near future.

5.1.3 Types of experimental designs applied

The review of on-farm trials carried out in Uganda between 1997 and 2001 revealed that the most common experimental design applied in on-farm trials in Uganda is a randomized complete block design (RCBD). All the forty experiments applied the RCBD (Table 5.2). Seventeen of out 40 used the RCBD with a split-plot arrangement, one used it with strip plot arrangement and the other twenty-two used ordinary RCBD (Table 5.2).

Table 5.2: Commonly used experimental designs in on-farm trials conducted in Uganda between 1997 - 2001

		Number of trials with	
Type of Design	Freq.	less than 5 treatments	5 to 10 treatments
RCBD (Ordinary)	22	18	4
RCBD with split-plot	17	10	7
RCBD with strip plot	1	1	0
Total	40	29	11

The researchers seem to be more comfortably with RCBD probably because it is easier to setup in the field, and to analyze since it is not different from what they use in on-station experimentation. Using farm as a complete block appears to be more appealing and convenient to researchers as it is easier to setup and to analyze using packages like MSTATC which is readily available. Furthermore, the most common and easy to read statistical literature dwell more on completely randomize designs(CRD) and RCBD. The frequent (17 out of 40) use of split-plot arrangement may be due to inclusion of many treatments/treatment combinations (Table 5.2) in the trials, or, putting emphasis on some treatments. Twenty-nine trials had less than five treatments per trial while 11 trials had between 5 and 10 treatments each. No trial had more than 10 treatments and of the 11 trials with more than 5 treatments per trials, 7 had split plot arrangement. Many statisticians/biometricians have argued for fewer (less than 5) treatments for on-farm trials so as to make the farmers not to loose track about what is being done. The use of designs such as balanced incomplete block (IBD) could lead to the reduction in the number of treatments per farm and would be much more efficient. However, the overly use of RCBD suggests lack of proper understanding on behalf of researchers about IBD.

5.1.4 Plot sizes

Eight reports did not have any information on the plot sizes used in the trials, 12 trials used plot sizes ranging between 40 and 50 m^2; 16 used between 20 and 30 m^2 and 4 had plot sizes between 10 and 20 m^2 (Table 5.3). These plot sizes are not different from the ones used in on-station trials in Uganda indicating that researchers are transferring the same practices to on-farm trials. Lack of land and other resources have been cited as some of the factors that limit plot sizes. In most cases the farmers are not willing to sacrifice big pieces of land for the experimental purposes (Akizza pers. com).

Table 5.3: Plot sizes used in on-farm trials in Uganda

Plot size (m^2	Number of trials
10-20	4
20 -30	16
30-40	0
40- 50	12
Not indicated	8
Total	40

5.1.5 The number of farms and replicates per farm

In most trials treatments were not replicated within farm/site, but instead the farms were used as replicates. Replication within farm increases the size of land which the farmers should sacrifice for the trials, and in most cases either this land is not available or the farmer is not willing to give it. If the farmer is the one to manage the trial, this will also interfere with management routine of the farmer for his/her other activities.

In on-farm trials which involved less than 5 farms there were at least 3 replicates within farm whereas trials with more than 5 farms had mainly a single replicate per farm/site (Table 5.4). Replication within farm in trials involving more than 10 farms becomes more expensive in terms of time and other resources such as land. This can explain why a single replicate is often used for experiments with many treatments.

Table 5.4: Number of farms and replicates within farm/site in trials

		No. rep within farm and corresponding freq.			
No. of farms per trials	No. of trials	1	2	3	4
Less than 5	15	0	0	14	1
5 - 10	18	18	0	0	0
11 - 15	0	0	0	0	0
Above 15	7	6	1	0	0
Total	40	24	1	14	1

5.1.6 Methods of analysis

All the analyzes of the 40 trials reviewed were carried out using traditional analysis of variance (ANOVA), and the treatment means were compared using the least significant difference (LSD). Only one researcher used multiple regression in addition to traditional ANOVA. All the researchers except one ignored interaction between treatments and farms, and even the one who appreciated the presence of interaction did not do any statistical analysis on it. The use of ANOVA stems from the fact that this is the method most commonly used in on-station experiments and most of the researchers are well acquainted with it, and the most used statistical package in agricultural research in Uganda is MSTATC, easily performs analysis of variance. The disadvantage with this analysis of variance is that it fails to isolate interaction between treatment and farm when there is no replication within the farm, the latter is the most common occurrence in on-farm trials. This interaction in most cases masks the treatment effects by increasing the size of the random error leading to non-significance of the treatment effects.

The analyzes of all the 40 trials indicated high variability which remained unexplained. Those reports which quoted the coefficient of variation (CV) values, the highest recorded was 350% (Table 5.5) indicating that either there was lack of precision or there was a lot of unexplained variability. The latter is more likely to be the case.

Table 5.5: Range of maximum CV obtained from 40 on-farm trials conducted in Uganda between 1997 - 2001

Range of maximum CV (percent)	Number of trials.
10 - 20	1
21 - 40	4
41 - 60	8
61 - 100	10
Above 100	1
No CV given	16
Total	40

These CV values were very high compared to the accepted level of less than 20% (Harvey pers.com). This is not surprising given the various sources of variability in on-farm trials.

In the sections that follow methods, i.e. mixed model approach, AMMI and AA that can handle variability to enable efficient analysis of on-farm trials are presented and used.

5.2 Examples

Three on-farm trials' data from Uganda are used for illustration of mixed model, AMMI and AA methods. The procedures entail studying the hierarchal structure of the data and variability at the different levels, and estimating variability using different models. Assessing variability involves assessing the contribution of the different sources of variability to the total variability in the observed response. In the present study, PROC MIXED in SAS (SAS Institute, 2001) was used in the illustrations (PROC MIXED used restricted maximum likelihood (REML) estimation method) for fitting mixed models. Additive main effect and multiplicative interaction models were fitted using AMMI procedure (under the directive "analysis of multiple experiments") in Genstat (Genstat Release 6.2), whereas AA was carried out using the linear regression procedure in Genstat Release 6.2 (6th edition)). It is to be noted that these three approaches, i.e. mixed model, AMMI and AA are complementary.

5.2.1 Example 1: Cotton trial SAARI - 1998

This trial was conducted by SAARI in 1998 on 36 farms in 9 districts of Uganda. The main aim of the trial was to evaluate the effect of different planting spacings (population) on cotton performance (yield and quality of cotton bolls). The trial spanned 2 districts in the north and 4 in the east, and 2 districts in west and one in the central part of the country. Due to biophysical similarities, districts from the north and east were classified as region I districts and those from the west and central as region II. Six spacings/plant populations were involved, and these included farmer's practice, old recommendations for region I and region II, and three (3) new recommendations (see appendix A 1). The management of the trials was left entirely to the farmers. The analysis was carried out on yield in kilogram per hectare (kg/ha)

Estimation of variance components

In this setup, assuming farms were selected at random from each district, and district were also selected at random from the regions, there are 5 levels at which variability occurs namely at region, district, farm and plot levels (.i.e. between regions, districts within regions, farms within districts and plots within farms). Interest, therefore would be to explore variability at the different levels in order to answer questions such as:

- which level has the highest contribution to the total variability?
- can we assume homogeneity of variance within a given level (for example districts within regions, farms within districts or farms within regions)?
- at what level can data analyzes be combined (region, district, etc) or combined at all the levels?
- which are the most appropriate random effects to include in the final model?

In all the models we assumed that the district and farm effects, and the interaction terms involving them were random while region and spacing effects were fixed. To answer all

the above questions we need to fit a series of sub-models of the general model given below. Consider a general model for a trial:

$$y_{ijkl} = \mu + \tau_i + \gamma_j + d_k + f(d)_{ljk} + \gamma\tau_{ij} + d\tau_{ik} + f\tau_{il}(jk) + \epsilon_{ijkl} \tag{5.1}$$

where y_{ijkl} is an observation from the ith spacing, in the lth farm in the kth district from the jth region, μ is overall mean, τ_i is the ith spacing effect, γ_j is the effect of the jth region, d_k is the effect of the kth district, $f(d)_{ljk}$ is the lth farm effect nested in the kth district in the jth region, the other terms are interactions among the main effects and ϵ_{ijkl} is the error term. The terms $f(d)_{ljk}$, $f\tau_{il}$, d_k, $d\tau_{ik}$, and ϵ_{ijkl} are assumed to be iid normal with means 0 and variance components σ^2_f, $\sigma^2_{f\tau}$, σ^2_d, $\sigma^2_{d\tau}$, and σ^2 respectively.

The following sub-models of the general model 5.1 are used to explore variability in the data

1. $y_{ijkl} = \mu + \tau_i + \gamma_j + \gamma\tau_{ij} + \epsilon_{ijkl}$ (fixed effects model)

2. $y_{ijkl} = \mu + \tau_i + \gamma_j + f(d)_{ljk} + \gamma\tau_{ij} + \epsilon_{ijkl}$ (σ^2_f is homogenous in all districts)

3. $y_{ijkl} = \mu + \tau_i + \gamma_j + f(d)_{ljk} + \gamma\tau_{ij} + \epsilon_{ijkl}$ ($\sigma^2_{f_l}$ is non homogenous in all districts)

4. $y_{ijkl} = \mu + \tau_i + \gamma_j + f(\gamma)_{lj} + \gamma\tau_{ij} + \epsilon_{ijkl}$ ($\sigma^2_{f_j}$ is non homogenous in all regions)

5. $y_{ijkl} = \mu + \tau_i + \gamma_j + d(\gamma)_{jk} + \gamma\tau_{ij} + \epsilon_{ijkl}$ (σ^2_d is homogenous in all regions)

6. $y_{ijkl} = \mu + \tau_i + \gamma_j + d(\gamma)_{jk} + \gamma\tau_{ij} + \epsilon_{ijkl}$ ($\sigma^2_{d_j}$ is non homogenous in all regions)

7. $y_{ijkl} = \mu + \tau_i + \gamma_j + d(\gamma)_{jk} + f(d)_{ljk} + \gamma\tau_{ij} + \epsilon_{ijkl}$

8. $y_{ijkl} = \mu + \tau_i + \gamma_j + d(\gamma)_{jk} + f(d)_{ljk} + \gamma\tau_{ij} + d\tau_{ik} + \epsilon_{ijkl}$

The main differences between models 2, 3, and 4 are the assumptions made about the between-farm variability each model. In model 2 the between-farm variability is assumed to be constant in all the districts whereas in 3 and 4 the between-farm variability is assumed to be non homogenous in the districts and regions respectively. In model 5 we assumed that between-district variability is homogenous in the two regions whereas in

Table 5.6: Estimates of variance component for the yield from the cotton trial

Models	Variance components	Estimates	% contribution	Fit statistics
1	Residual	595151	100	-2*l* = 3324.8 AIC = 3326.8 AICC = 3326.8 BIC = 3330.1
2	a)farm(district) b)residual	482831 112320	81.13 18.87	-2*l* = 3096.4 AIC = 3100.4 AICC = 3100.5 BIC = 3103.6
3	a) farm(district) district 1 district 2 district 3 district 4 district 5 district 6 district 7 district 8 district 9 b) residual	 88892 748492 155760 123363 129110 252369 272023 1850870 588694 112324	81.13 18.87	-2*l* = 3081.0 AIC = 3101.0 AICC = 3102.2 BIC = 3116.8
4	a) farm (region) region 1 region 2 b)residual	 541894 318766 112320	81.13 18.87	-2*l* = 3095.6 AIC = 3101.6 AICC = 3101.8 BIC = 3106.4
5	a) district(region) b) residual	99713 520197	16.09 83.91	-2*l* = 3309.2 AIC = 3313.2 AICC = 3313.2 BIC = 3313.6
6	a) district(region) region 1 region 2 b) residual	 71674 191930 519577	16.09 83.91	-2*l* = 3308.7 AIC = 3314.7 AICC = 3314.7 BIC = 3315.3
7	a) farm(district) b) district(region) c) residual	482829 0 112321	81.13 00.00 18.87	-2*l* = 3096.4 AIC = 3100.4 AICC = 3100.5 BIC = 3103.6
8	a) farm(district) b) district(region) c) dist*treatment d) residual	482875 0 1376.43 111196	81.13 0.00 0.23 18.64	-2*l* = 3096.4 AIC = 3102.4 AICC = 3102.5 BIC = 3107.1

model 6 between-district variability is assumed to be non homogenous in the two regions. Models 7 and 8 are based on the assumptions of models 2 and 5 (variability of farm within districts and districts within regions are constant).

The fixed effects model (model 1, Table 5.6) forms the basis for assessing the importance of the different random effects (see Section 4.1.3). Model fit statistics were used. From Table 5.6, model 1 is associated with -2loglikelihood (-2l) value of 3324.8 while model 2 has 3096.4. Thus addition of farm effect to fixed effects model is associated with (a change in -2loglikelihood of 228.4 (3324.8 - 3096.4)). This change in -2l (228.4 on 1 degree of freedom (df)) is significant. This indicates the importance of between-farm variability as a major cause of variation in the observed responses (yield in kilogram per hectare). Between farm variability alone accounted for about 81.13% (% contribution $= \frac{\text{variance component}}{\text{Total of variance components estimates}} \times 100$) of total observed variability in the response (see Table 5.6). The difference in values of -2loglikelihood (-2l) between models 2 and 3 enables the test for heterogeneity of between-farms variability in the 9 districts. From Table 5.6 model 3 is not significantly different from model 2 (change in -2loglikelihood of 15.4 (3096.4 - 3081.0) on 8 (10 - 2) degrees of freedom), thus we can conclude that overall statistically between-farms variance is constant in the 9 districts. Although statistically between farm variances are constant in the 9 districts, closer inspection indicate that three districts (2, 8 and 9) have very high between-farm's variability compared to other districts. Similarly the difference in the values of -2loglikelihood between model 2 and model 4 tests for heterogeneity of between-farms variability in the two regions. Based on the change in the -2loglikelihood (0.8 on 1 degree of freedom) between models 2 and 4 it is clear that between farm variability was constant in the two regions, although there appear to be more variation in region 1.

The contribution of between districts variability to the total observed variability was very low (see variance components of models 5, 6, 7 and 8). This is not surprising given that the majority of the districts are from one region and have similar biophysical characteristics (districts are administrative units). Thus, district as a level of variability does

not capture much variability (16.09% see model 5 and 6). Variability between districts in the regions was constant as evidenced by the -2loglikelihood of models 5 and 6.

Based on the change in -2loglikelihood, model 2 is the best model for the data.

Based on the above results the following suggestions are given;

- If similar trials are to be conducted in future, there would be need for increasing the number of farms instead of districts so that the different farm conditions are represented (since between farm variability had the highest contribution to the total variability in response). In particular districts 2, 8 and 9 should have more farms investigated compared to other districts since the farms in those districts vary greatly.

- Data from districts 2, 8 and 9 should be analyzed separately whereas the rest analyzed as a unit. This is because these districts (2, 8 and 9) show very high variability compared to others and thus they would have more influence on the result of the analysis and makes the finding unreliable.

- More attention needs to be put in finding out the main causes of the high variability between farms.

Between farm variability has been identified as the main contributor to the total variability in the observed responses. The main question to be answered is 'how can we account for this variability?' Differences in management practices or biophysical factors such soil characteristics, rainfall, temperature, etc could be responsible for the large between farm variability. Information on the various factors recorded at farm level could be of great help in explaining this. In this study only information on two management practices, i.e. planting date and pesticide applications used were available. Both pesticide used (used as a factor) and number of days (used as covariate) from the earliest planting (1^{st} June) were introduced into the mixed model but both did not have any significant effect ($p = 0.2598$ and 0.5451) on the yield (Appendix A 3).

Thus, in summary using a mixed model is more efficient in identifying and modelling variability at the different levels in an on-farm trial. The hierarchical stages through which mixed models are built up leads to efficient evaluation of each level. It also allows for use of subsidiary information in modelling.

Application of AMMI

On the assumption that the 36 farms were representative of different cotton growing environments in Uganda, AMMI enables us to explore the interaction that exist between these farm environments and the treatments (plant spacings). The results of analysis of variance using the AMMI model are in Table 5.7. The results indicate that farm

Table 5.7: AMMI analysis of cotton yield

Source	df	SS	MS	F	P
Treatments	5	3091959	618392	10.11	0.0000
Farms	35	103082236	2945207	48.15	0.0000
Block	-	-	-	-	
Interactions	175	20481215	117036	1.91	0.0025
IPCA1	39	7733243	198288	3.24	0.0000
IPCA2	37	6692512	180879	2.96	0.0001
Residuals	99	6055459	61166		
Error	0	0	-	-	
Total	215	126655410	-		

and spacing (treatment) accounted for 81.39% and 2.44%, respectively, of the total sums of squares (% contribution $= \frac{\text{sum of square due effect}}{\text{total sums of squares}} \times 100$), while the interaction plus error accounted for the remaining 16.17%. This is an indication that more variation was due to farm and farm-by-spacing interaction than spacing alone. The basic analysis of variance indicated that the spacing, farm and first 2 interaction principle components or IPCA's (see section 4.2.1 for explanation on principle components) are significant ($p = 0.0000$, 0.0000, 0.0000, 0.0001, respectively Table 5.7). The F-test in this case was done using the residual after decomposition of interaction sums of squares as the error term. It should be noted that testing of main effect is not of concern since this can be done using the traditional analysis of variance.

The first 2 IPCA's can explain about 70.43% (total % contribution of sums of squares of the first 2 IPCA) of the variability due the interaction effects. We can use the biplot of the first 2 IPCA's to visualize interaction between spacing and farms (environment). The biplot explained about 95.22% ($\frac{\text{sums of square due to spacing, farms and first 2 IPCAs}}{\text{total sums of squares}} \times 100$) of total observed variability, and thus can give effective interpretation of main effects of spacing, farms and their interaction. The biplot allows us to visualize any relationship between the six plant spacings and the farms. The displacement from the center of the biplot exhibits differences in interaction (Manrique and Hermann, 2000). The results in Figure 5.1 show that the different plant spacings respond differently to the different farm conditions. The biplot (Figure 5.1) revealed that plant spacings 2, 4 and 5 are least interactive, indicating a broad adaptability, while high interaction was shown by plant spacings 1, 6 and 3. Plant spacing 6 (S6) showed high specific adaptability to farms with large negative IPCA1 scores (E27, E7 and E18) while plant spacing 3 (S3) showed specific adaptability to farms with positive IPCA2 scores (E20, E1 and E5) and plant spacing 4 (S4) does not showed specific adaptability to any particular farm environment. Plant spacing 1 showed specific adaptability to farms with negative IPCA2 scores. Based on the biplot one can group farms according to the adaptability of the different plant spacings. For example, farms E27, E7, E6 could be put in one recommendation domain (suitable for plant spacing 6) whereas E33, E26, E16 E23 could also be put in another group (suitable for plant spacing 1) etc. In this way AMMI with its biplot cautions researchers against giving general recommendations based on maximum overall yield. There is need to characterize farms in the different recommendation domains so that the same recommendation can be applied to other farms with similar characteristics.

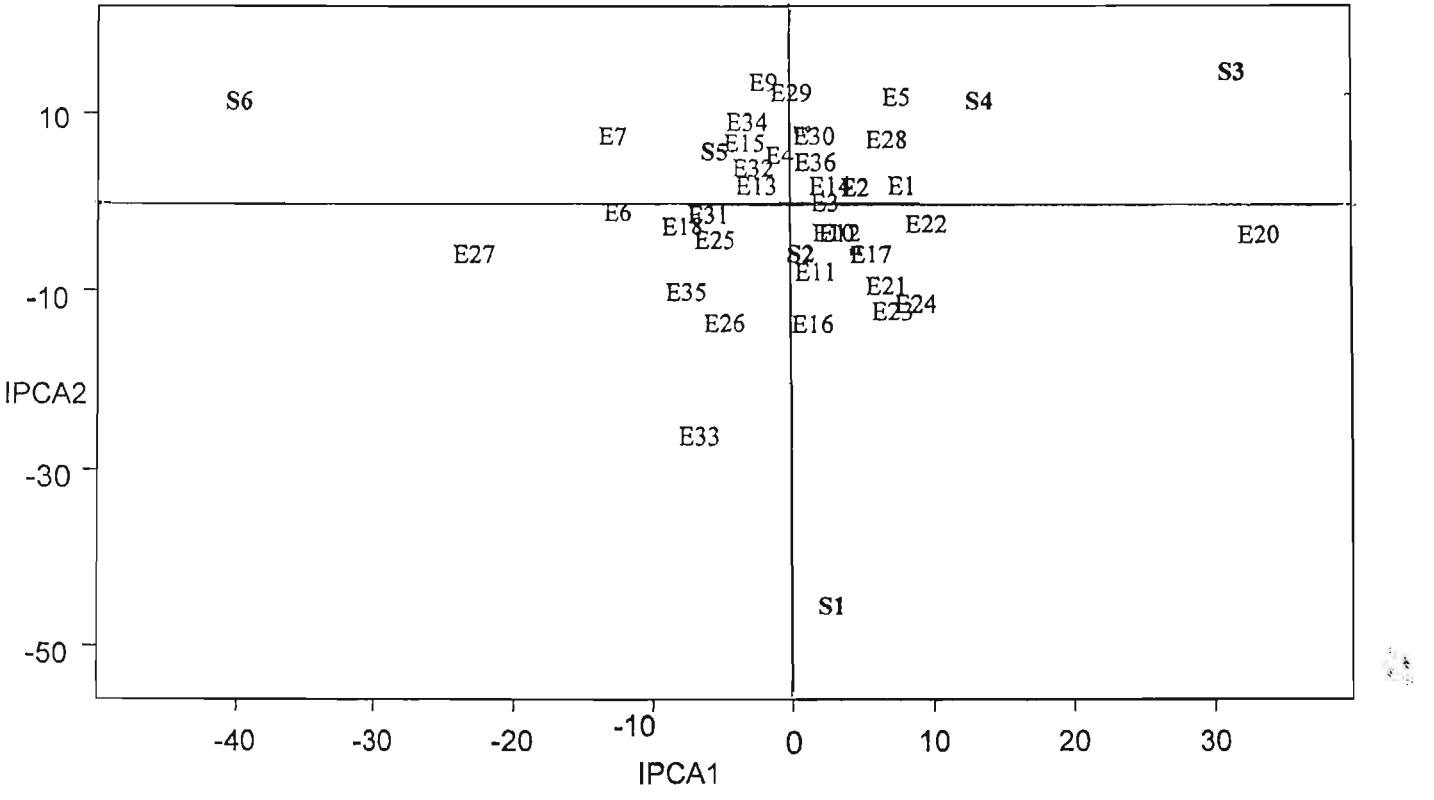

Figure 5.1: Biplot of interaction principal components analysis(IPCA) axis 2 vs. axis 1 for cotton yield

Application of modified stability analysis

If we assume that the farmers did not alter their usual practices, then the farmers had only the six plant spacings being tested in common. Each farmer subjected the plant spacings to different soil conditions, planting dates, pest control methods, fertilizers and other management practices. The average yield from all the six plant spacings in a given farm acts as an estimate of that farm's capacity to produce cotton using the different plant spacings being tested (in this case the best environment for cotton is farm 26; Appendix A4). This average is what is referred to as environmental index (EI). The ratio of the range of EI to the mean of EI is used as a measure of the representativeness of the farms used in the trial. For this particular trial the ratio of the range of EI to the mean of EI is 2.98. This indicates that a very broad sample of farm environments was included in the cotton trial. Given that the distribution of EIs (see Appendix A4) is quite uniform over the 'poor' and 'good' farm environments this trial meets the requirement stated in Section 4.2.2 (i.e. one could expect any observed relationships between plant spacings and farms to be consistent over time). We can relate the response for each plant spacing to the environmental index by simple linear regression below:

$$y_{ij} = \alpha_i + \beta x_j + \epsilon_{ij} \tag{5.2}$$

$i = 1, 2, \ldots, t;\ \ j = 1, 2, \ldots, f;$

where y_{ij} is yield from the ith spacing in the jth farm, x_j is the jth farm/site index.

By fitting the above model independently for each spacing and examining the slope, the adaptability (stability) of the spacings were determined (Table 5.8). The regression coefficients of all the plant spacings are close to 1 thus they all have similar level of adaptability. Plant spacing 1 ($\beta > 1$) would be expected to perform much better in high yielding environments whereas the reverse should be true for plant spacing 3 based on their β_i values. All the R_a^2 values indicate that linear model give a good description of relationship between plant spacings and environmental indices. The plot of fitted values from linear regression against EI (Figure 5.2) expressed a clear linear relationship between

Table 5.8: Estimates of Regression parameters for Cotton-Spacing Stability Analysis

Spacing	constant(α_i)	adaptability parameter(β_i)	Standard error	R_a^2
1	-97.0	1.2052	0.0894	83.8
2	20.9	0.9174	0.0520	89.9
3	86.0	0.8952	0.0933	72.2
4	-84.9	0.9072	0.0495	90.6
5	-39.8	0.9832	0.0430	93.7
6	116	0.9782	0.1030	71.8

yields and environmental indices. The performance of all the plant spacings increases with improvement in environmental conditions and this increase was highly marked in plant spacing 1. Although spacing 1 was superior in most environments, it performed very poorly in low yielding environment and was outperformed by plant spacing 6 in low-yielding environments (EI < 1000).

In terms of cotton yield therefore, Figure 5.2 suggests that the researcher could have two recommendation domains, i.e. those suitable for plant spacing 1 and those for plant spacing 6. However at low yielding environments there were no clear differences between the performance of all planting spacings. In order to characterize the two (high and low yielding environments) likely recommendation domains we need biophysical or socioeconomic variables measured at farm level. For this data set only two variables (planting dates and pesticide used) were available. Neither planting dates nor insecticide used showed a clear relationship with environmental index (see also AMMI illustration above) and thus can not be used to characterize the farms in the two recommendation domains.

We can use the yield of farmers' practice (plant spacing 4) to define the two recommendation domains. Those farmers who expect to get cotton yield below 1200 kg/ha (using their usual plant spacing) could use plant spacing 6 and the rest of the farms could use plant spacing 1. The analysis of variance can be used to verify the existence of the two domains. The combined ANOVA across the two domains confirmed that the two domains are significantly different but the interaction between treatment and domain was not significant(i.e. the apparent rank interchange between plant spacings 1 and 6 observed in Figure 5.2 could have been purely due to chance) (Appendix A5). The lack of

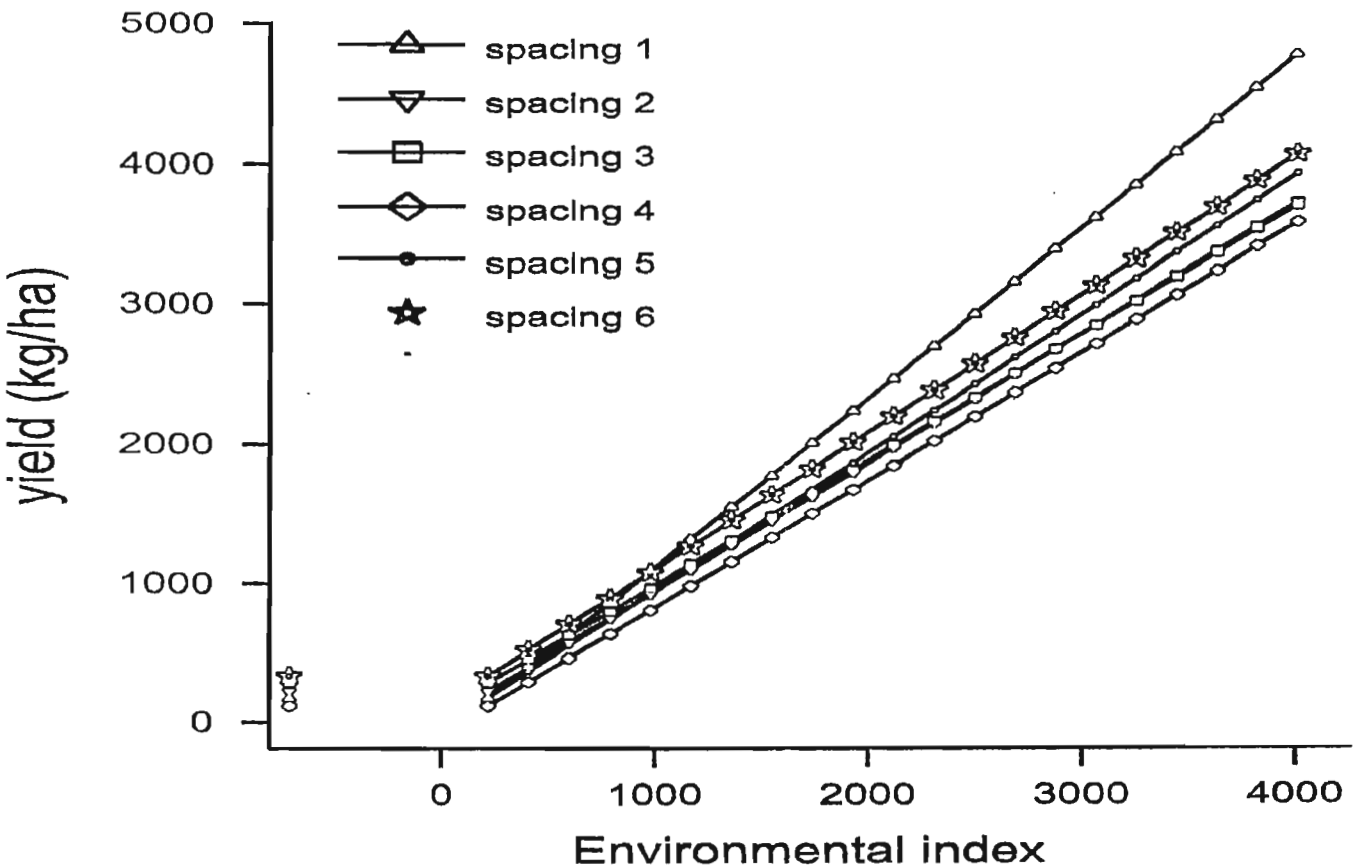

Figure 5.2: Fitted value vs EI (regression lines for cotton spacings)

interaction between treatment and the recommendation domains could be due to the fact that overall all plant spacings performed poorly in the poor environment (differences in performance are only observed in the good environment). In this case it is quite difficult to give recommendation in the low yielding environment. However, all farmers could be recommended to use cotton spacing 1 but could be advised to follow some agronomic practices that improve their farm conditions so as to get higher yield (yield increases with improvement in farm conditions). It should also be noticed from Figure 5.2 that plant spacing 4 has merged together with plant spacing 2 (the two spacings are identical in their performance in all environments).

5.2.2 Example 2: Maize variety - fertilizer trials -1997

Namulonge agricultural and animal production research institute (NAARI) carried out maize variety - fertilizer trials on twelve (12) farms in four districts (Mbale, Iganga, Mpigi and Masindi) of Uganda. Each farm acted as a replicate of a randomize complete block design. The districts were taken as representatives of the maize growing districts of Uganda. The treatments were five maize varieties denoted as A, B, C, D, E and two levels of N-fertilizer denoted as 1 and 2 resulting in 10 variety-fertilizer combinations (defined as: T1 = A + 1, T2 = B + 1, T3 = C + 1, T4 = D + 1, T5 = E + 1, T6 = A + 2, T7 = B + 2, T8 = C + 2, T9 = D + 2 and T10 = E + 2). The response variable measured was maize yield in tons/hectare (t/ha). The management of the trial was left entirely to the farmers.

Estimation of variance components

Assuming the farms were selected randomly from each district, there are three levels at which variability occurs (plot, farm and district levels), i.e. between districts, farms within districts and plots within farms. Exploration of variability at each of these levels is of main interest in this study.

The general model for this trial can written as:

$$y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + d_l + f(d)_{kl} + f\alpha_{ik(l)} + d\alpha_{il} + f\beta_{jkl} + d\beta_{jl} + \epsilon_{ijk} \qquad (5.3)$$

$i = 1, 2, 3, 4, 5;\ j = 1, 2;\ k = 1, 2, ..., 12;\ l = 1, 2, 3, 4$

where y_{ijkl} is the yield of the ith variety, receiving the jth level of fertilizer, in the kth farm in the lth district, μ is the overall mean, α_i is the ith variety effect, β_j is the effect of the jth level of fertilizer, $f(d)_{kl}$ is the effect of the kth farm nested in the lth district, d_l is the lth district effect, $\alpha\beta_{ij}$, $f\alpha_{ik(l)}$, $d\alpha_{il}$, $f\beta_{jk(l)}$, $d\beta_{jl}$ are interaction terms and ϵ_{ijkl} is the random error. The random effects $f\alpha_{ik(l)}$, $f\beta_{l(j)}$, d_l, $d\alpha_{ik}$, $d\beta_{ik}$, $f(d)_{kl}$ and ϵ_{ijkl} are assumed to be *iid* normal with means 0 and their respective variance components are; $\sigma^2_{f\alpha}$, $\sigma^2_{f\beta}$, σ^2_d, $\sigma^2_{d\alpha}$, $\sigma^2_{d\beta}$, σ^2_{fd} and σ^2.

Variability in this trial was explored using the following sub-models of the general model (5.3);

1. $y_{ijk} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + \epsilon_{ijk}$ (fixed effects model)

2. $y_{ijkl} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + f(d)_{kl} + \epsilon_{ijk}$ (σ^2_f is homogenous in all districts)

3. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + f(d)_{kl} + \epsilon_{ijk}$ (σ^2_{fl} is non homogenous in all districts)

4. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + d_l + \epsilon_{ijk}$

5. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + d_l + f(d)_{kl} + \epsilon_{ijk}$

6. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + d_l + f(d)_{kl} + f\alpha_{ik(l)} + \epsilon_{ijk}$

7. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + d_l + f(d)_{kl} + f\beta_{jk(l)} + \epsilon_{ijk}$

8. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + d_l + f(d)_{kl} + d\alpha_{il} + \epsilon_{ijk}$

9. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + d_l + f(d)_{kl} + d\alpha_{il} + d\beta_{jl} + \epsilon_{ijk}$

10. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + d_l + f(d)_{kl} + d\alpha_{il} + f\beta_{jk(l)} + f\alpha_{ik(l)}d\beta_{jl} + \epsilon_{ijk}$

Table 5.9: Variance components at various levels in the maize-variety trial

Models	Variance components	Estimates	% contribution	Fit statistics
1	Residual	0.2485	100	-2*l* = 404.3 AIC = 406.3 AICC = 406.3 BIC = 409.0
2	a)farm(district) b)residual	1.2211 0.6218	66.26 33.74	-2*l* = 318.0 AIC = 322.0 AICC = 322.2 BIC = 323.0
3	a) farm(district) district 1 district 2 district 3 b) residual	 0.8756 0.8904 1.1907 0.6218	66.26 33.74	-2*l* = 311.6 AIC = 319.6 AICC = 320.0 BIC = 321.6
4	a) district b) residual	0.5497 1.4431	27.58 72.42	-2*l* = 382.9 AIC = 386.9 AICC = 387.0 BIC = 385.1
5	a) farm(district) b) district c) residual	0.9856 0.3239 0.6218	51.10 16.77 32.13	-2*l* = 317.4 AIC = 323.4 AICC = 323.6 BIC = 324.9
6	a) farm(district) b) district c) farm*fertilizer c) residual	0.9856 0.3238 0 0.6218	51.10 16.77 00.00 32.13	-2*l* = 317.4 AIC = 323.4 AICC = 323.6 BIC = 324.9
7	a) farm(district) b) district c) farm*variety c) residual	0.9570 0.3239 0.2575 0.3928	49.55 16.77 13.33 20.35	-2*l* = 308.8 AIC = 316.8 AICC = 317.2 BIC = 318.8
8	a) farm(district) b) district c) district*variety c) residual	0.9931 0.3006 0.1160 0.5467	50.76 15.36 05.93 27.95	-2*l* = 312.6 AIC = 320.6 AICC = 321.0 BIC = 322.6
9	a) farm(district) b) district c) district*variety d) district*fertilizer e) residual	0.9937 0.2938 0.1168 0.0134 0.5409	50.74 15.00 05.96 00.68 27.62	-2*l* = 312.5 AIC = 322.5 AICC = 323.0 BIC = 324.9
10	a) farm(district) b) district c) farm*variety d)farm*fertilizer c) district*variety e) residual	0.9658 0.3065 0.1983 0.0075 0.0867 0.3853	49.64 15.75 10.19 00.00 04.46 19.57	-2*l* = 307.3 AIC = 319.3 AICC = 320.1 BIC = 322.2

Again in this case farm effect still had the highest contribution to the total variability in the response (Table 5.9). Between farms variability accounted for 66.26% of the total variability (models 2 and 3). Based on the comparison of model 2 and 3, the between farm variability in this trial was significantly different ($p = 0.0401$) in the three districts (change in the value of -2loglikehood of 6.4 (318.0 - 311.6) with 2 degrees of freedom). Between farms variability in district 3 was about 1.5 times that in district 1 and 2 and this could imply that combined analysis over the three districts may not be quite suitable (Table 5.9). District also captured appreciable amount of variability. When the trial was collapsed over the districts (i.e. districts used as a blocking factor), 27.58% of variability was accounted for by district effect compared to 15.03% in the cotton trial in example 1. District effect remained prominent in all the other models (Table 5.9). The three districts are in different parts of the country and could have different biophysical characteristics such as rainfall, temperature, soil properties. The interaction between variety and farm also had a considerable contribution to the total observed variability (models 7 and 10). This seems to suggest that the response of the variety is not constant/the same over the different farms (environments). The interaction terms involving fertilizer had negligible contribution to the total variability in the responses. The model fit statistics suggest that the best covariance model is model 3.

Application of AMMI

This trial can be examined in terms of the 10 variety-fertilizer treatment combinations or each factor (variety and fertilizers) separately. Additive main effect and multiplicative interaction models can help us to understand the nature of any interaction that exist between treatments and the environments represented by the farms. We have only discussed the result of the 10 variety-fertilizer treatment combinations and the five varieties. The analysis of variance of the AMMI model for the yield of the 10 treatment combinations (Table 5.10) show significant differences of treatment and farms' main effects, and IPCA 1 and 2 (p = 0.0000, 0.0000, 0.0000 and 0.0316, respectively). The first two IPCA's explain about 65% of the total variability. The F values were calculated using the residual

Table 5.10: Analysis of variance for AMMI model for variety-fertilizer combination

Source	df	SS	MS	F	P
Treatments	9	32.52	3.613	10.60	0.0000
Farms	11	141.16	12.833	37.63	0.0000
Block	-	-	-	-	
Interactions	99	61.55	0.622	1.82	0.0368
IPCA1	19	26.75	1.408	4.13	0.0000
IPCA2	17	13.30	0.782	2.29	0.0316
Residuals	63	21.50	0.341		
Error	0	0.00	0.000		
Total	119	235.23			

as the error term and their values were compared with the F-table values. The biplot (Figure 5.3) of the first two significant axes (IPCA1 and IPCA2) for the yield show that all the 10 variety-fertilizer treatment combinations and all the 12 farms are dispersed around the center of the biplot, indicating high variability in treatment combinations and farms. Most variety-fertilizer treatment combinations are far from the center of the biplot indicating specific adaptability to certain farm environments. The least interactive variety-fertilizer combination is T1 (variety A + fertilizer level 1) followed by T4 (variety D + fertilizer level 1). Highest interactions were shown by combinations T9, T3, T8, T5, T10, T6 and T2. Treatment combination T9 showed specific adaptability to farms E9 and E10, treatment combinations T3 and T8 showed specific adaptability to farms E2

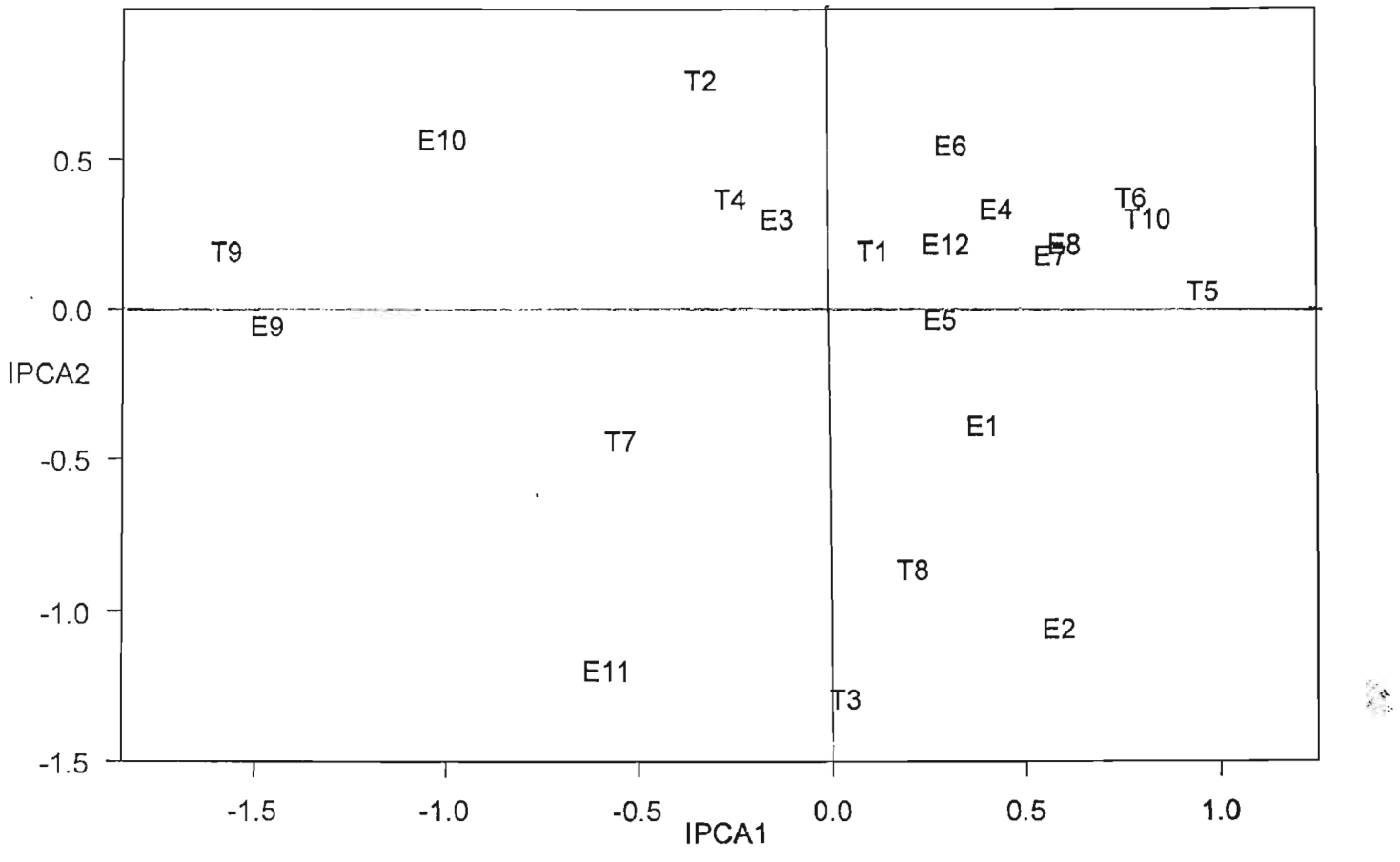

Figure 5.3: Biplot of interaction principal components analysis (IPCA) axis 2 vs. axis 1 for variety-fertilizer treatment combinations yields

and E11 whereas T5, T6 and T10 seem to be favored in farms E7 and E8.

In case we are only considering variety (ignoring fertilizer, i.e. assume the fertilizer effect is not of importance), fertilizer levels provide error degrees of freedom for the testing of variety and farm main effects as well as their interaction and the IPCA's (due to the hidden replicate in the factorial design associated with variety-fertilizer trials).

Table 5.11: Analysis of variance for AMMI model for varieties

Source	df	SS	MS	F	
Variety	4	26.02	6.505	13.89	0.0000
Farms	11	141.16	12.833	27.42	0.0000
Block	-	-	-	-	
Interactions	44	39.95	0.908	1.94	0.0087
IPCA1	14	21.60	1.543	3.29	0.0006
IPCA2	12	10.67	0.889	1.90	0.0525
Residuals	18	7.67	0.426	0.91	0.5699
Error	60	28.10	0.468		
Total	119	235.23			

The first two IPCA's were significant and explain 80.78% of the total variability due the interaction effects. The biplot of the IPCA1 and IPCA2 for the yield show a similar pattern of dispersion to that in Figure 5.4. Variety A appears to be the least interactive among all the varieties. Variety C has the highest interaction with farms followed by D, E and B. Variety C showed specific adaptability to farms E1, E2 and E11 whereas varieties D and B appears to be favored by farms E9 and E10. The least interactive (most stable) farms are E5 and E4. The relationships obtained from the biplot together with additional information measured at farm level can be utilized in understanding the nature of interaction in non-replicated on-farm trials.

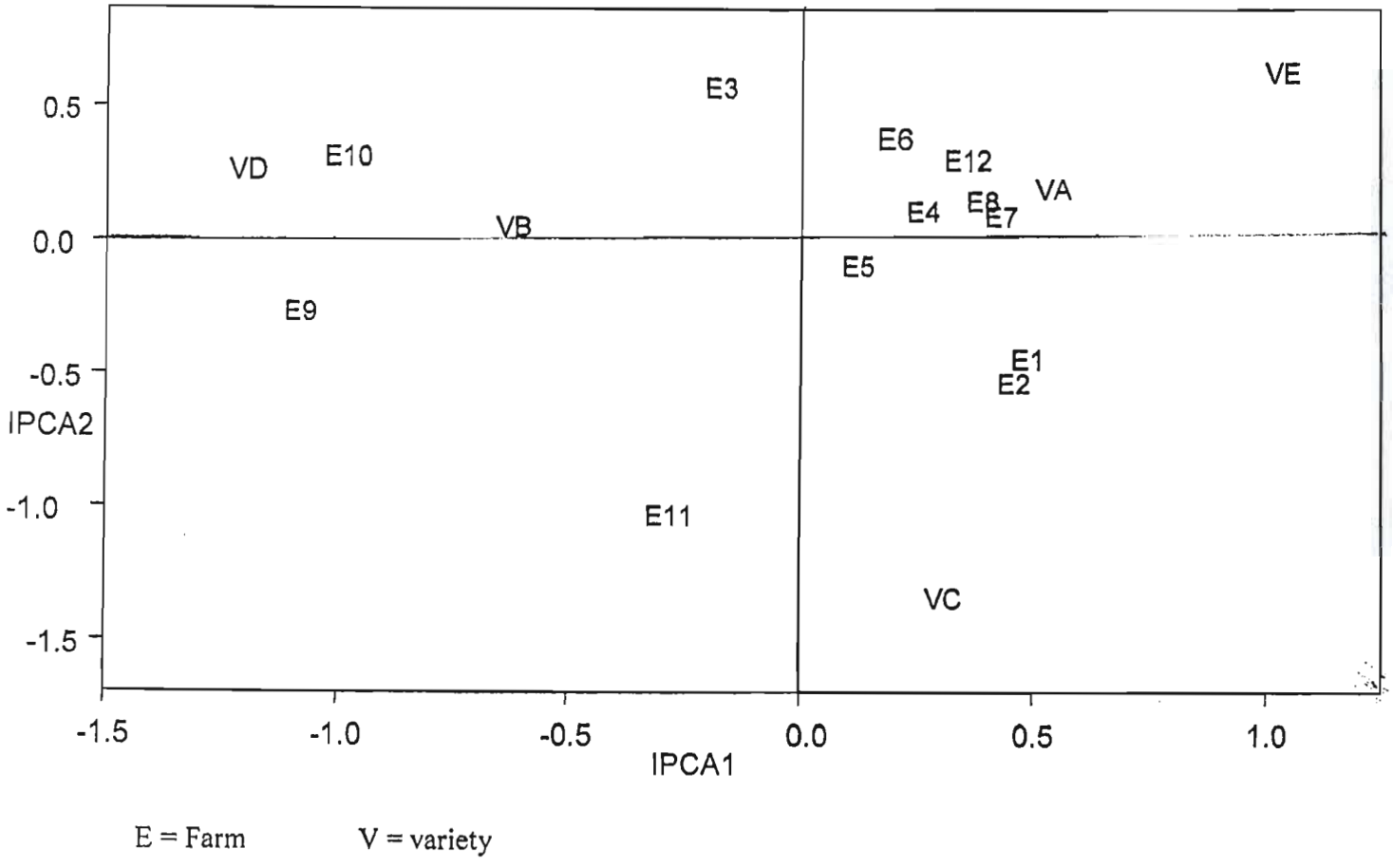

Figure 5.4: Biplot of interaction principle components analysis (IPCA) axis 2 vs. axis 1 for variety yield

Application of Stability analysis

Based on the assumption that the farmers did not alter their usual practices, then the farms only had the different variety-fertilizer combinations being tested in common. The environmental index (EI) in this case is an estimate of each farm's potential to produce maize under the different variety-fertilizer combinations. The farm with the highest EI is considered the best environment for maize production using the various variety-fertilizer combinations (farm 9 would be considered the best environment and farm 8 the worst environment for maize production (Appendix B 3)). In this data set the ratio of range of EI to mean of EI is only 0.73 indicating that a narrow sample of environments was tested. The selected environments may not represent the maize growing farms in other parts of Uganda. This result should therefore be interpreted with caution since the data does not meet all the three criteria for AA (see Section 4.2.2). The yield from each of the ten (10) variety-fertilizer combinations can be related to the environmental index using a simple linear regression:

$$y_{ij} = \alpha_i + \beta_i x_j + \epsilon_{ij} \tag{5.4}$$

$i = 1, 2, \ldots, t;\ \ j = 1, 2, \ldots, f;$

where y_{ij} is the yield of the ith variety-fertilizer combination, x_j is the environmental index for the jth farm. The index is as defined in Section 4.2.2.

Table 5.12: Adaptability (stability) statistics for variety-fertilizer combinations

Combinations	constant(α_i)	adaptability parameter(β_i)	Standard error	R_a^2
T1	0.954	0.802	0.146	72.5
T6	1.15	0.702	0.211	47.7
T2	0.574	0.950	0.193	67.9
T7	-0.925	1.394	0.110	93.5
T3	-1.426	1.358	0.195	81.2
T8	-0.433	1.171	0.161	82.5
T4	-0.383	0.986	0.145	80.2
T9	-2.120	1.535	0.263	75.0
T5	1.198	0.552	0.179	43.8
T10	1.412	0.550	0.145	54.8

The values of β_i (Table 5.12) for the various variety - fertilizer combinations indicate

their adaptability to the range of environments presented. The combinations T5 and T10 (variety E and fertilizer levels 1 and 2) are highly adapted to low yielding environments whereas combinations T7 (variety B and fertilizer level 2), T3 (variety C and fertilizer level 1) and T9 (variety D and fertilizer level 2) are highly suitable for high yielding environments. The other combinations with β_i values much closer to 1 generally do not show specific adaptability to any environment. To simplify the analysis and make it more visual, the levels of fertilizer can be separated. Plotting the yields across EIs for all five varieties at each level of fertilizer (Figures 5.5 and 5.6) allows one to visualize the response of maize varieties at each fertilizer level.

At fertilizer level 1 there is a rank interchange between variety B and C, i.e. variety B was superior in 'poor' environments (EI $<$ 4.9) whereas variety C was superior in 'good' environments. Variety C particularly performed very poorly in very low yielding environments and this agreed with the high β_i value (1.358) observed for combination T3 (Table 5.12). Thus under fertilizer level 1 we can define two recommendation domains for each of varieties B and C. Variety B was superior in all the environments under fertilizer level 2 (Figure 5.6) and this signifies a single recommendation domain for it. It is also visually clear from Figure 5.6 that as environmental conditions improve (environment becomes suitable for maize production) the yield gap between varieties B and D closes but that between B and C widens under fertilizer level 2. Under both fertilizer levels 1 and 2 variety E was inferior compared to others on most farms except in very low yielding environments (combinations T5 and T10 had very low regression coefficient values Table 5.12). Whether to give one or two recommendation domains will depend on the level of fertilizer used by the farmers. However, as stated before, the adaptability analysis result of this trial should be interpreted with caution since the range of environments tested is narrow according to the criteria in Section 4.2.2.

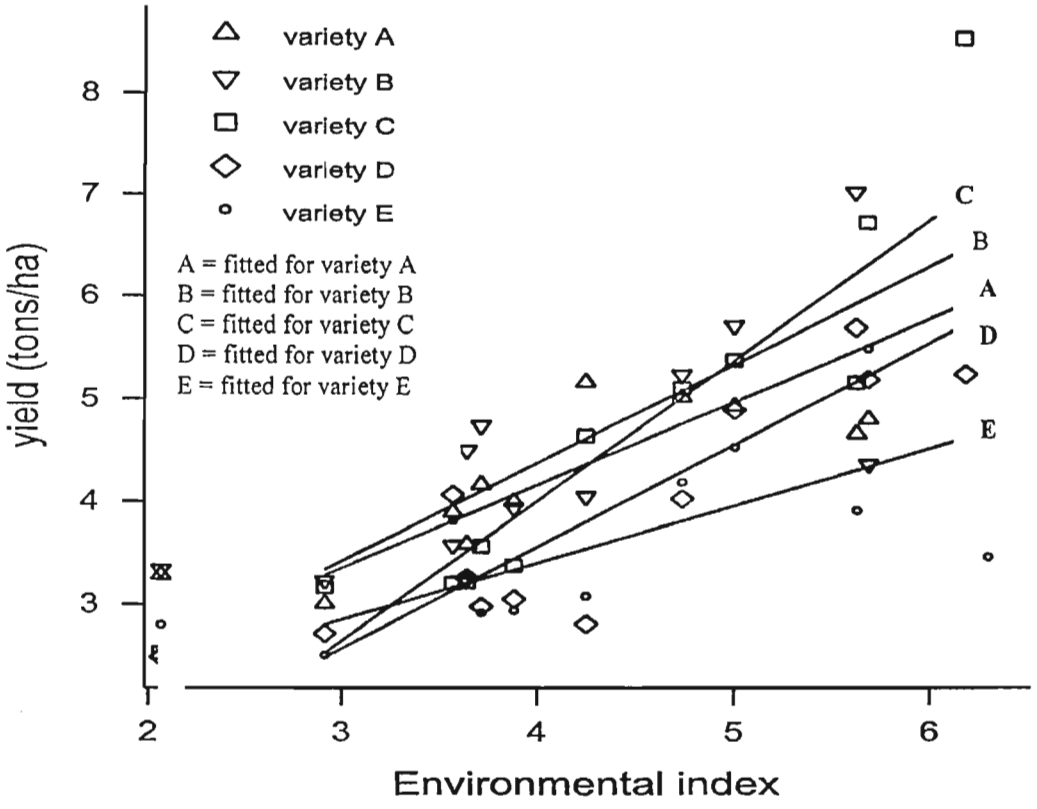

Figure 5.5: Plot of yield vs farm index for varieties at fertilizer level 1

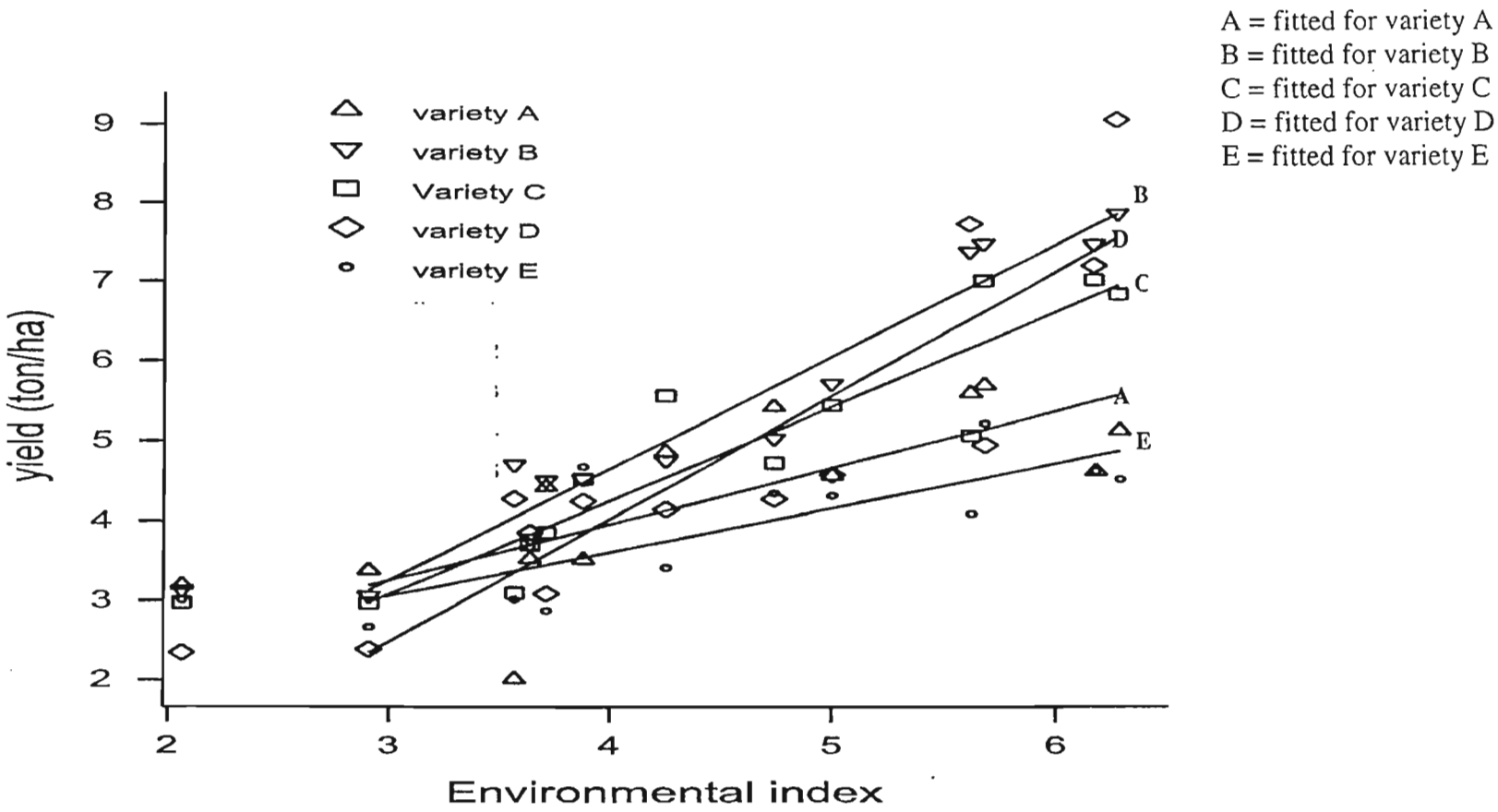

Figure 5.6: Plot of yield vs farm index for varieties at fertilizer level 2

5.2.3 Example 3: Integrated nutrient management in sweet potatoes production - 2001

This trial was setup by a Postgraduate student (MSc. Agriculture) from Makerere university in Kumi district in eastern Uganda. Fourteen (14) farms were selected at random from five (5) villages and each farm acted as a replicate of a randomized complete block design. The trial was conducted in two seasons (different sets of farmers were used in each season). The treatments involved were combinations of green manure (GM) (*Mucuna sp.*) and mineral fertilizers phosphorous (P) and potassium (K). The seven (7) green manure-mineral fertilizer combinations were; absolute control (no organic manure or mineral fertilizer), GM (relative control), GM + $11kgha^{-1}P$, GM + $22kgha^{-1}P$, GM + $35.5kgha^{-1}P$, GM + $71kgha^{-1}K$ and GM + $11kgha^{-1}P$ + $35kgha^{-1}K$.
Response variables measured include: tuber weights (total, marketable and non-marketable weights) and biomass of sweet potatoes. Only the analysis of total weight (kilogram/hectare (kg/ha)) is discussed in this study. The student's interest was mainly on yield response of sweet potatoes to the 7 treatment combinations. Although the trial was designed as RCBD, some treatments were lost in some farms (i.e. some farms did not have measurement for all the 7 treatment combinations)

Estimation of variance components

In this trial plots were nested within farms, farms within villages and farms were also nested within seasons. In this study the interest is the estimation of variance components at farm and village levels as well as within season.

Consider the general model

$$y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + f(v)_{kl} + v_l + f\beta_{jk} + f\alpha_{jk} + v\beta_{jk} + \epsilon_{ijkl} \qquad (5.5)$$

where y_{ijkl} is an observed response from the ith treatment combination, in the jth season from the kth farm in village l, μ is the over-all-mean, α_i is the ith treatment effect, β_j is the jth season effect, $f(d)_{kl}$ is the effect of the kth farm nested in the lth village, v_l is

the lth village effect, ϵ_{ijkl} is the random error and the remaining terms are interactions between the main effects. The random components $f(d)_{kl}$, $f\alpha_{ik}$, $f\beta_{jk}$, v_l, $v\beta_{ik}$ and ϵ_{ijk} are assumed to be *iid* normal with means 0 and variance components σ_f^2, $\sigma_{f\alpha}^2$, $\sigma_{f\beta}^2$, σ_v^2, $\sigma_{v\beta}^2$ and σ^2 respectively.

To estimate variance components at the different levels the following sub-models of model (5.5) can be used.

1. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + \epsilon_{ijkl}$ (fixed effects model)
2. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + f(v)_{kl} + \epsilon_{ijkl}$ (σ_f^2 is homogenous in all villages)
3. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + f(v)_{kl} + \epsilon_{ijkl}$ ($\sigma_{f_l}^2$ is not homogenous in all villages)
4. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + f(\beta)_{jk} + \epsilon_{ijkl}$ ($\sigma_{f_j}^2$ is not homogenous in all seasons)
5. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + v_l + \epsilon_{ijkl}$
6. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + f(v)_{kl} + v_l + \epsilon_{ijkl}$
7. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + f(v)_{kl} + v_l + v\alpha_{ik} + \epsilon_{ijkl}$
8. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + f(v)_{kl} + v_l + f\alpha_{jk} + \epsilon_{ijkl}$
9. $y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + f(v)_{kl} + v_l + f\alpha_{jk} + v\alpha_{jk} + \epsilon_{ijkl}$

Models 5, 6, 7, 8 and 9 are based on the assumptions of model 2.

Table 5.13: Variance components at various levels in the sweet potatoes trial

Models	Variance components	Estimates	% contribution	Fit statistics
1	Residual	113.31	100	-2l = 924.3 AIC = 926.3 AICC = 926.3 BIC = 929.1
2	a)farm(village) b)residual	73.606 57.797	55.89 44.11	-2l = 872.7 AIC = 876.7 AICC = 876.9 BIC = 877.9
3	a) farm(village) village 1 village 2 village 3 village 4 village 5 b) residual	 146.320 7.357 47.632 283.630 62.455 57.438	55.89 44.11	-2l = 865.7 AIC = 877.7 AICC = 878.4 BIC = 881.1
4	a) farm(season) season 1 season 2 b) residual	 139.200 23.748 57.581	55.89 44.11	-2l = 869.5 AIC = 875.5 AICC = 875.5 BIC = 877.2
5	a) village b) residual	76.64 80.36	49.77 50.23	-2l = 894.9 AIC = 898.9 AICC = 899.0 BIC = 898.2
6	a) farm(village) b) village c) residual	37.91 62.82 57.72	23.93 39.65 36.42	-2l = 869.5 AIC = 875.5 AICC = 875.5 BIC = 877.2
7	a) farm(village) b) village c) village*treatment c) residual	40.22 59.14 10.15 50.22	25.18 37.02 06.35 31.45	-2l = 867.1 AIC = 875.1 AICC = 875.5 BIC = 877.4
8	a) farm(village) b) village c) farm*treatment c) residual	37.68 63.29 3.35 54.70	23.67 39.76 02.22 34.35	-2l = 871.2 AIC = 879.2 AICC = 879.5 BIC = 881.4
9	a) farm(village) b) village c) farm*treatment d) village*treatment c) residual	40.22 59.18 0.00 10.15 50.22	25.18 37.02 00.00 06.35 31.45	-2l = 867.1 AIC = 875.1 AICC = 875.5 BIC = 877.4

The between farm variability in the absence of other random effects accounted for 55.89% of the total variability observed (model 1, Table 5.13). Model 3 indicate that the between farm variability was higher in villages 1 and 4 compared to others and similarly model 4 suggest that it was high in season 1 compared to season 2. However, comparing the values of -2loglikelihood of both models 3 and 4 with that of model 2, the change in -2loglikelihood (7 (872.7 - 869.7) on 1 degree of freedom for model 3 and 3.2 (872.7 - 869.5) on 1 degree of freedom for model 4) indicate that between farm variability was constant both within village and season (see section 4.1.3). A possible reason for apparent high variability in the first season could be that in the first season most farmers are always involved in many agricultural activities compared to second season thus leading to more variability in the former. Village effect also had a high contribution to the total variability (see models 5 to 9 Table 5.13). The high between villages variability could have resulted from socioeconomic differences. Farmers living in the same neighborhood tend to behave in a similar way. The contribution of the interaction terms to total variability was quite low. Models 8 and 9 have the same values of fit statistics thus are not statistically different. Model 8 can be taken as the best model (since the contribution of farm*treatment is negligible). We still need variables measured at both farm and village level in order to be in position to account for the observed variation. The student should have taken more records of non-experimental variables.

5.3 Conclusion

A large number of researchers/research institutions in Uganda are involved in on-farm trials. However, most researchers still try to minimize the degree of farmer's involvement in those trials. That is only 22.5% of the trials were managed entirely by farmers. This could be due to fear of introducing high variability through farmers' involvement. The designs and analysis of most on-farm trials in Uganda are still based on the conventional on-station research methods (proposed designs such as incomplete blocks and other unbalanced designs are not being used). The most common method of analysis used in on-farm

trial is the traditional ANOVA and the multilevel nature of these trial are ignored in analysis. Very little efforts are made to estimate variability at the different levels in those trials.

The illustrations in this chapter showed that mixed model approach can be used successfully to explore and quantify variability at the different levels in on-farm trials. In all the three on-farm trials used for illustration, variability between farms was the main cause of variation in the observed response. The information provided by the researchers were generally insufficient to explain the variability at the different levels.

We can also conclude that both AMMI and AA are very useful in understanding treatment-by-farm interaction in non-replicated on-farm trials through both their estimated parameters and graphical representation. Both are similar and may be used to determine appropriate recommendation domains.

Chapter 6

Conclusions

Involvement of farmers and the use of their fields/farms or animals in the on-farm trials result in the introduction of high variability from various sources. In agronomic trials, variability comes from four main sources; plant genotype, management practices, socioeconomic factors and crop environment. Sources of variability from animal on-farm trials can broadly be classified as environmental and genetic. Environmental variation can be due to differences in biophysical factors (rainfall, temperature, etc), or management practices (feeding, health care, housing etc). All the above sources of variability are encountered by on-farm researchers in Uganda.

Most on-farm trials are hierarchal in nature (have multilevel structure) e.g. plots/animals nested within farms, farms nested within villages and villages nested within agro-ecological zones. The above sources of variability (plant genotype, management, etc) cause variations at each of those levels (plot, farm, village, etc). The different sources of variability dictates the type of variables (indicator variables) to be measured or recorded in on-farm trials. The indicator variables help in explaining the importance of different sources of variability in the trial. The information recorded at each level in the trial can be used either in designing or in the analysis of the trial. Variability at each of those levels contributes to the total variability in the observed response. It is important therefore to estimate variability associated with those levels for proper designing and understanding of the trial result.

The case study indicated that a large number of researchers/research institutions in

Uganda are involved in on-farm trials. However, most researchers still try to minimize the degree of farmer's involvement in those trials (only 22.5% of the trials reviewed were managed entirely by farmers). This could be to avoid introducing high variability by farmers' involvement. The designs and analysis of most on-farm trials in Uganda are still based on the conventional on-station research methods (proposed designs such as incomplete blocks and other unbalanced designs are not being used). The most common method of analysis used in on-farm trial is the traditional ANOVA and the multilevel nature of these trials are ignored in analysis. Very little efforts are made to estimate variability at the different levels in those trials.

For estimation of variability in on-farm trials mixed model approach is preferred. The distributional assumptions of the random terms in the traditional analysis of variance (linear model) is too restrictive. The assumptions of zero correlation and homogeneity variance are most often violated in on-farm trial and these assumptions put severe limitation on application of traditional ANOVA in such trials. The applicability of traditional ANOVA in on-farm trial is restricted to balanced experiment with limited amount of missing observations. Mixed model on the other hand does not require the trial to be balanced and allows for both correlation and heterogenous variances as part of the model. Mixed model in particular is more suitable for multilevel trials compared to the traditional ANOVA approach. The illustrations (Section 5.2) showed that mixed model approach can be used successfully to explore and quantify variability at the different levels in on-farm trial. In all the three on-farm trials used for illustration, variability between farms was the main cause of observed variability in observed response. When farm are nested in villages, districts or seasons, between farm variability tended to be different in the different groups.

In non-replicated on-farm trials interaction between the farms (environment) and treatment/technology can also contribute tremendously to the variability observed in the response. In conventional on-station statistical methods, this interaction can only be tested when there is replication within the farms. Additive main effect and multiplica-

tive interaction(AMMI) model and adaptability analysis (AA) provide us with options for understanding this interaction without the need for within farm replication. Graphical representation from these two methods provides simple method for understanding farm-by-treatment interaction.

The main lesson learnt from examples discussed in Section 5.2 is that for proper understanding of on-farm trials we need to use more than one statistical tool. Mixed model for example enables researchers to know the contribution of the various levels in the trial to the total observed variation. The combined use of AMMI, AA and traditional ANOVA can help researchers to put farm environments into more homogenous groups on which the recommendation will be given. It becomes easier to explain the causes of variability in the trial by concentrating on levels identified by mixed model as the main contributor of variation observed. For example, in the case where between farm variability is the main contributor to the total variability, the main task would be to try to understand the relationship between non-experimental variables recorded at farm level with the response.

Although mixed models have been suggested as the best alternative for estimation of variability in on-farm trial, the main problem encountered in using this approach is lack of convergence. This problem becomes more pronounced as the number of levels in the trial increases. The performance of mixed model under various on-farm scenarios should be assessed. The effect of methods for selection of farmers, villages or other levels to be included in on-farm trials is another area for further research. In mixed models we assume the farms and villages are selected at random but most often farmers are chosen based on their willingness to participate in the trials. There is need to assess the validity of results based on non random selection of farmers and villages.

Extensive studies on application of mixed models in on-farm trials needs to be done. Much emphasis should be put on the effects of farmers' selection, sample sizes (number of farms to be included in the trials)and number of levels (farm, village, agro-ecological zones, etc) to be included in the model.

Bibliography

Ames, D.R. and Ray, D.E. 1983. Environmental muanipulation to improve animal productivity. *Journal of Animal Science* 57:209-220.

Anon. 1996. Nation environemtal management Authority (NEMA). State of the environment report for Uganda.

Byerlee, M.D., Collinson *et al.*, 1980. Planning technologies appropriate to farmers: concepts and procedure. CMMYT, EL Batan, Mexico

Carpenter, J.R. 1998. Complexity of animal's environment and its stressors. http://www.hawaii.edu/ansc/News/95summer/envstres.htm

Coe, R. and Franzel, S. 1995. Designing on-farm experiments. Report for workshop held at ICRAF, Nairobi, Kenya 26-29 June 1995.

Collinson, M.P. 1987. Farming system research procedures. *Experimental Agriculture* 23: 370 - 386

Cooper, M., Delacy, I.H. and Basford, K.E. 1996. Relationships among analytical methods used to analyse genotype adaptation in multi-environment trials. *In Plant and crop improvement.* Cooper, M and Hammer, G.L.(Eds), pp.193-224. CAB International Wallingford, U.K.

Corbel, R.R. and Searle, S.R. 1976. A comparison of variance estimators. *Biometrics* 32:779-791.

Dobson, A.J. 1990. An introduction to generalized linear models 1st edition. London: Chapman and Hall.

Eberhart, S.A. and W.A. Russell.1966. Stability parameters for comparing varieties. *Crop Science* 6:36-40.

Eremie, S.W, P.S.O. Okoli and H.R. Chheda. 1991. An assessment of the design and analysis of on-farm trials in Nigeria's Agricultural Development Projects (ADPs). *In On-farm research in theory and practice.* Eds H.J.W. Mutsaers and P. Walker. IITA.

Ibadan, Nigeria, p 102-108.

Euwijk, F.A.van. 1995. Multiplicative interaction in generalized linear models. *Biometrics* 51:1017-1032.

FAO-UNESCO, 1978. "Report on the Agro-Ecological Zone Project," Food and Agriculture Organization and United Nations Educational, Scientific and Cultural Organization, World Soil Resources Report 48, Rome, Italy.

Fielding, W.J. 1990. Review of experimental design in a developing country: A case-study from Jamaica. Field crop research 24:241-250.

Finlay, K.W. and Wilkison, G. N. 1963. The analysis of adaptation in a plant-breeding programme. *Australian Journal of Agricultural research* 14, 742 - 754

Francis, A.C. 2002. Credibility of on-farm research in future information network. http//www.ianr.unl.edu/cari/csas/vol3-6.htm.

Freeman, G.H. 1973. Statistical methods for the analysis of genotype-environment interaction. *Heridity* 31:339-354.

Gabriel, K.R. 1971. Biplot display of multivariate matrices with application to principal component analysis,*Biometrika* 58: 453-467.

Gauch, G.H. Jr. 1990. *AMMI and related analysis of two-way data matrices.* Department of Agronomy Cornel University.

Goldstein, H. 1986. Multilevel mixed linear model analysis using iterative generalized least squares, *Biometrika* 73: 43-56.

Hartley, H.O. and Rao, J.N.K. 1967. Maximum likelihood estimation for the mixed analysis of variance model. *Biometrika* 54: 93-108.

Harville, D.A. 1977. Maximum likelihood approaches to variance component estimation and to related problems. *Journal of the American Statistical Association* 72: 320-340

Henderson, C.R. 1975. Best linear unbiased estimation and prediction under a selection model, *Biometrics* 31:423-447

Henderson, C.R., 1950. Estimation of genetic parameters (Abstract). *Annals of Mathematical Statistics* 21: 309-310

Hildebrand, P.E., 1984. Modified Stability Analysis of farmer managed on-farm trials. *Agronomy Journal* 76: 271-274.

Hildebrand, P.E., and J.T. Russell. 1996.*Adaptability analysis. A method for the design, analysis and interpretation of on-farm research-extension.* Iowa State University Press.

Horgan, G.W. and Hunter, E.A. 1993. *Introduction to REML for scientists.* Scottish Agricultural Statistical Service.

Jiggins, J. 1989. Farmer participatory research and technology development. *Occasional Papers in Rural Extension No.5.* Department of Rural Extension, University of Guelph , Ontario Canada.

Kackar, R. N. and Harville, D.A. 1984. Approximation of for standard errors of estimators of fixed and random effects in a mixed model, *Journal of American Statistical Association* 79: 853 - 862.

KARI. 1994. Kenya Agricultural Research Institute annual report.

Korie, S. and R.U. Okechukwu. 1999. Analyses of on-farm and augmented trials with mixed model. *In Biometry and quality of life:Proceeding of the sixth scientific workshop of the Sub-Saharan Africa Network (SUSAN) of the International Biometric Society (IBS).* Ed. Nokoe, S. Ibadan: Nigeria.

Levin, J.B. 1999. The use of variance component models in the analysis of complex surveys. PhD. Thesis, University of Natal.

Lin, C.S., Bins, M.R. and Lefkovitch, L.P. 1986. Stability analysis: where do we stand? *Crop Science* 26:894-900.

Littell, R.C., Milliken, G.A., Struop, W.W. and Wolfinger, R.D. 1996. *SAS System for Mixed Models, SAS Institute Inc.*, Cary, NC.

Lockeretz, W. 1987. Establishing the proper role of for on-farm research. *American Journal of Alternative Agriculture* 2:132-136.

Mackenzie, D.R., Mills, W.R. and Watts, J.O. 1976. Predicting yield and processing quality of potato breeding selections. *American Potato Journal* 53: 87 - 98.

Manrique, K. and Hermann, M. 2000. CIP program report 1999 - 2000. CIP, Lima, Peru.

McCallagh, P. and Nelder, J. A. 1989. Generalized linear models 2nd edition. London: Chapman and Hall.

McCulloch, C. E. and Shayler, R. Seare 2001. *Generalized, linear, and mixed models.* New York: Wiley.

Mclean, R. A., William, L. S., and Stroup, W. W. 1991. A unified approach to mixed models. *The American Statistician* 45:1, 54-63

Milliken, G.A. and Johnson, D.E. 1989. *Analysis of messy data, Vol. 2: Nonreplicated Experiments.* Van Nostrand Reinhold, NY.

Mutsaers, H.J.W., Smith J., and Walker, P. 1991. A synopsis of workshop conclusions. *In On-farm research in theory and practice.* Eds H.J.W. Mutsaers and P. Walker. IITA. Ibadan, Nigeria, p 1-19.

Mutsaers, H.J.W and Walker, P. 1990. Farmer's maize yields in South Western Nigeria and the effect of variety and fertilizers: An analysis of variability in on-farm trials. *Field Crop Science Research* 23: 265-278.

Mutsaers, H.J.W., Weber, G.K., Walker, P. and Fischer, N.M. 1997. *A field Guide for On-Farm experimentation* IITA/CTA/ISNAR

NARO. 2002. National Agricultural Research Organisation (Uganda). http://www.naro.go.ug

Njuho, P.M. and Chui, J.N. 1999. Understanding on-farm trials variability through coefficient of variation. *Journal of Tropical Forestry* (Special issue: Biometry and Quality of life) 15:76-83.

Njuho, P.M., and Milliken, G.A. 1995. Mixed model approach to no-farm trials: An alternative to Meta-analysis for comparing on treatment to possible different controls. *Proceedings of the 1995 Kansas State University Conference on Applied Statistics in Agriculture*

Nokoe, Sagary. 1999. On-farm trials: Surgical or preventive approach. *Journal of Tropical Forestry* (Special issue: Biometry and Quality of life) 15:76-83.

Okali, J.S. and Farrigton, J. 1994. *Farmer participatory research by: Rhetoric and reality.* Intermediate technology publications 103-105 Row, London WC1B4HH, UK.ODI 1994.

Oyejola, B.A. 1999. An overview of on-farm trials: *Journal of Tropical Forestry* (Special issue: Biometry and Quality of life) 15:76-83.

Patternson, H.D. and Thompson, R. 1971. Recovery of interblock information when block sizes are unequal. *Biometrika* 58:545-554.

Riley, J. and Alexander, C. 1997. "Statistical Literature for Participatory on-farm Research". *Experimental Agriculture* 33: 73-82.

Riley, J. and Fielding W.J. 2001. An illustrated review of some farmer participatory research techniques. *Journal of Agricultural, Biological and Environmental techniques* 6 (1).

Robinson, D. L. 1987. Estimation and use of variance components. *The statistician* 36: 3- 14.

Robinson, G. K. 1991. That BLUP is a Good Thing: The estimation of random effects. *Statistical Science* 6 : 1, 15-51.

SAS Institute Inc. 1996. *SAS/STAT Software: Changes and enhancement through release 6.12.* Cary, NC: SAS Institute Inc.

SAS Institute Inc. 1999. *SAS/STAT Software: Changes and enhancement through release 8.2.* Cary, NC: SAS Institute Inc.

Satterthwaite, F.E. 1946. An approximate distribution of estimates of variance components. *Biometrics Bulletin* 2:110-114.

Scones, I. 1996. Crop production in a variable environment: A case study from Southern Zimbabwe. *Experimental Agriculture* 32:291-303.

Searle, S.R., Casella, G. and McCulloch, C.E. 1992. *Variance Components.* New York: Wiley.

Shafii, B. and Williams J. P. 1998. Analysis of genotype-by-environment interaction using additive main effect and multiplicative interaction model and stability estimates. *Journal of agricultural biological and environmental statistics*(Special issue: Resource selection using data from GIS) 3, (3): 335-342.

Statistical Service Center, 2001(a). Modern approach to the analysis of experimental data. htt://www.rdg.ac.uk/ssc/dfid/booklets/topaed.html.

Statistical Service Center, 2001(b). Mixed model and multilevel data structure in agriculture. htt://www.rdg.ac.uk/ssc/dfid/booklets/topmix.html.

Stroup, W.W., Hildebrand, P.E. and Francis, C.A. 1991. Farmer participation for more effective research in sustainable agriculture. *Food and resource dept. staff paper SP91-32.* University of Florida. Gainesville, FL.

Sumberg, J. and Okali C. 1988. Farmers, on-farm research and the technology development. *Experimental agriculture* 24:333-342.

Verseteeg, M.N., and Huijsman, A. 1991. Trials design and analysis for on-farm adaptive research: A 1988 maize trial in the Mono Province of the Republic of Benin.

In On-farm research in theory and practice. Eds H.J.W. Mutsaers and P. Walker. IITA. Ibadan, Nigeria, p 111-121.

Appendix A

Cotton trial

A.1 Detail of treatments in the SAARI cotton trial 1998

Spacing	Row width (cm)	Within row (cm)	Population (plants/ha)	Type of practice
6	60	30	111111	Old recommendation for East & North
5	90	30	74074	Old recommendation for Central & West
4	90	45	49382	Farmer's
3	90	25	88888	New recommendation 1
2	75	30	88888	New recommendation 2
1	75	15	88888	New recommendation 3

A.2 SAS PROC MIXED program used for estimating variability in cotton trial

```
Data Cotton;
input region district farm days chemical spacing yield ;
cards;

     1      7      20     13      1      1    1990
     1      7      16     15      1      1    2240
     1      7      34     13      1      1     795
     .      .      .      .       .      .      .
     .      .      .      .       .      .      .
     .      .      .      .       .      .      .
     1      9      21     31      2      6    2300
```

```
      1       9      27      26       2       6    2300
      1       9      35      24       2       6    1707
      1       9       8      25       2       6     700;
Proc mixed;
     class region dist farm spacing;
     model yield = Spacing|region /ddfm=satterth;
Proc mixed;
     class region dist farm spacing;
     model yield = Spacing|region /ddfm=satterth;
     random  farmer(district);
Proc mixed;
     class region dist farm spacing;
     model yield = Spacing|region /ddfm=satterth;
     random  farmer(district)/group = district;
Proc mixed;
     class region dist farm spacing;
     model yield = Spacing|region /ddfm=satterth;
     random  farm(region)/group = region;
Proc mixed;
     class region dist farm spacing;
     model yield = Spacing|region /ddfm=satterth;
     random  farm(district) district district*treatment;
Proc mixed;
     class region dist farm spacing;
     model yield = Spacing|region /ddfm=satterth;
     random  farm(district) district;
Proc mixed;
     class region dist farm spacing;
     model yield = Spacing|region /ddfm=satterth;
     random  farm(district) district;
```

A.3 Output for testing effect planting date and pesticide used in cotton trial

```
        Covariance Parameter
           Estimates
 Cov Parm          Estimate
 farmer(dist)        491735
 Residual            112320

          Fit Statistics

-2 Res Log Likelihood          3075.1
AIC (smaller is better)        3079.1
```

AICC (smaller is better)	3079.1
BIC (smaller is better)	3082.3

Type 3 Tests of Fixed Effects

Effect	Num DF	Den DF	F Value	Pr > F
region	1	32	0.62	0.4367
treat	5	170	5.36	0.0001
region*treat	5	170	2.47	0.0345
chemical	1	32	1.32	0.2598
days	1	32	0.37	0.5451

A.4 Farm(environment) indices for the cotton trial

region	district	farm	index	region	district	farm	index
1	4	1	1551	2	2	19	1035
1	8	2	610	1	7	20	1977
1	1	3	960	1	9	21	2416
1	1	4	583	1	4	22	1093
2	6	5	1057	2	6	23	1435
2	3	6	1247	1	5	24	1332
2	6	7	1653	2	6	25	2411
1	9	8	857	1	8	26	4030
2	3	9	2025	1	9	27	1933
1	8	10	856	1	8	28	927
1	8	11	1570	1	7	29	789
1	4	12	1048	1	4	30	519
1	4	13	702	1	1	31	1405
2	2	14	315	1	1	32	1261
2	6	15	1106	1	5	33	1337
1	7	16	1486	1	7	34	999
2	3	17	1194	1	9	35	1515
1	5	18	542	1	7	36	222

A.5 ANOVA result for verifying the existence recommendation domain

```
120  "General Analysis of Variance."
121  BLOCK farm
122  TREATMENTS spacing*domain
```

```
 123  COVARIATE "No Covariate"
 124  ANOVA [PRINT=aovtable,information,means; FACT=32;\
            FPROB=yes; PSE=diff] yield

***** Analysis of variance *****

Variate: yield

Source of variation     d.f.       s.s.       m.s.      v.r.   F pr.

farm stratum domain        1     4.165E+07  4.165E+07  23.05 <.001
Residual                  34     6.144E+07  1.807E+06  15.33
spacing                    5     3.092E+06  6.184E+05   5.25 <.001
spacing.domain             5     4.441E+05  8.883E+04   0.75 0.584
Residual                 170     2.004E+07  1.179E+05
Total                    215     1.267E+08
```

Appendix B

Maize variety - fertilizer trial

B.1 SAS PROC MIXED programme used for estimation of variability NAARI maize variety-fertilizer trial

```
 Data maize;
  input district farm fertilizer variety yield;
  cards;

1   1   1   1   5.17
1   1   1   2   4.05
.   .   .   .   .
.   .   .   .   .
.   .   .   .   .
3   12  2   3   4.53
3   12  2   4   4.25
3   12  2   5   4.68 ;
Proc mixed;
     class  district farm fertilizer variety;
     model yield = fertilizer|variety/ddfm=satterth;

Proc mixed;
     class  district farm fertilizer variety;
     model yield = fertilizer|variety/ddfm=satterth;
     random farm(district);
Proc mixed;
     class  district farm fertilizer variety;
     model yield = fertilizer|variety/ddfm=satterth;
     random farm(district)/group = district;

Proc mixed;
     class  district farm fertilizer variety;
```

```
     model yield = fertilizer|variety/ddfm=satterth;
     random district;
Proc mixed;
     class  district farm fertilizer variety;
     model yield = fertilizer|variety/ddfm=satterth;
     random farm(district) district;
```

B.2 Farm (environment)indices for the maize variety-fertilizer trial

District	Farm	Index	District	Farm	Index
1	1	4.252	2	7	4.742
1	2	5.692	2	8	2.911
1	3	3.571	3	9	6.302
1	4	3.715	3	10	5.631
2	5	5.008	3	11	6.193
2	6	3.642	3	12	3.882