FACTORS COST EFFECTIVELY IMPROVED USING COMPUTER SIMULATIONS OF MAIZE YIELDS IN SEMI-ARID SUB-SAHARAN AFRICA

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ABSTRACT

Achieving food security is a challenge for the developed and developing world. These challenges are greater for developing nations such as in Africa because of the severity of the problems. An important aspect of this is poor agricultural productivity. Worldwide, technology is being developed to increase agricultural production. One aspect of this is the development of predictive computer models that enable farmers to optimise crops using management decision based on simulation scenarios. Most African farmers do not have the computer resources or expertise to implement these types of technology. Even extension offices in Africa, who provide much needed advice, can be under resourced in this way. We suggest here that simpler computer models that are cheaper and easier to use need to be developed. As a first step in this process we investigate here which factors are most cost effectively managed using computer simulations in semi-arid conditions pertinent to much of sub-Saharan Africa. Factors known to be important in crop farming are planting date, sowing density, variety, weeding, soils and fertiliser. We use qualitative arguments with simulations and conclude that interactions between rainfall, soil condition and fertiliser can benefit from simulations and thus should help in their management.

Keywords: modelling crop yields; small scale farming; food production

1.   INTRODUCTION

Small scale farming systems are characterised by poor investment in farming inputs, low productivity and widespread persistent poverty (Shumba, 1993; Rohrbach & Okwach, 1997; Selvaraju, Meinke & Hansen, 2004). One of the primary reasons for the low or poor crop yields are found to be a lack of relevant and adequate information necessary for making informed crop management decisions (Prasad, Kesseba & Singh, 1996; Masere, 2011). These decisions include crop types and variety choices, planting dates, sowing densities, fertiliser investment, and weeding frequencies. Getting these management variables right is key for small scale farmers to obtain optimal crop yields thus ensuring their food security and livelihood is enhanced.

Crop modelling platforms can offer decision support information to help farmers optimise crop yields. Moreover the crop models offer farmers the opportunity to assess and quantify risks associated with their operational management decisions under climate variations (Struif-Bontkes & Wopereis, 2003). If computer resources and expertise to operate them are not

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limited then any management factor could benefit from information provided by simulations. Many African farmers, however, do not have unlimited computer capacity. In fact most can only access technical support of this kind from extension offices. These extension offices also have limited computer support. Thus, we are suggesting that simplified model for helping crop management decisions need developing.

Past studies (Prasad et al., 1996; Beckford & Barker, 2007; Morton, 2007; Masere, 2011) have shown that in the absence of decision support mechanisms, like crop models, small scale farmers rely on their own experience to optimise crop yields, with some success. This experience involves tried and tested indigenous knowledge and the input of extension officers. Thus, crop models should best help management variables which farmers' indigenous knowledge and extension assistance cannot optimally address.

This study aims to identify and evaluate which crop management factors could potentially benefit from model predictions and which are more cost effectively left to experience in semi-arid conditions pertinent to much of sub-Saharan Africa.

There are many types of models ranging from simple to sophisticated, cheap to expensive. A key attribute of a model is its credibility in yield prediction. The most credible models are those that simultaneously incorporate and simulate processes involved throughout the course of crop growing season on a daily basis (Probert & Dimes, 2004; Masere, 2011). Thus, the model must consider soil conditions, climate conditions, crop growth processes and farmer's management strategies (fertiliser, weeding, sowing density). The Agricultural Production Systems Simulator (APSIM) package was chosen as it meets these criteria.

In this study the management of maize crop is considered because maize is an important staple food for many Sub-Saharan countries and is also grown throughout the world. It is also source of food and livelihood for millions of people (Auffhammer, 2011).

2.   METHODS

The research methodology involved qualitative and quantitative aspects of analysis. The qualitative aspect involved considering which variables might not benefit from extensive modelling without recourse to further investigation. Our own knowledge from previous work and existing literature were used to make these primary decisions. Other variables were explored using a quantitative approach (a computer model platform).

A crop modelling platform was used to assess pertinent management variables namely weeding, soil conditions, and fertiliser based on what might or not benefit from model simulations in providing information for farmers to optimise crop yields. APSIM version 7.4 was chosen as the modelling platform because it simulates crop growth processes based on climate, soil and management variables on a daily time step thus matching reality (Dimes, Twomlow & Carberry, 2003; Carberry, Gladwin & Twomlow, 2004; Probert & Dimes, 2004; Masere, 2011). APSIM has been validated in many farming systems of world including Africa (Dimes et al., 2003; Carberry et al., 2004). APSIM is a crop simulation model developed for accurate predictions of crop yields in line with climatic, environmental and management factors and also to move away from stand-alone crop models which were unable to simulate essential aspects of cropping systems (Keating, Carberry, Hammer, Probert, Robertson, Holzworth, Huth, Hargreaves, Meinke, Hochman, McLean, Verburg, Snow,

Dimes, Silburn, Wang, Brown, Bristow, Asseng, Chapman, McCown, Freebairn & Smith, 2003).

As explained in the results below fertilizer, soil and weeding were investigated using APSIM, and planting date, maize variety, and sowing were not. Thus, uniform data values with regards to planting date, maize variety, and sowing were applied for all simulations (Table 1). Planting date was chosen as 25th of October. Sowing density is based on results found by Medeiros & Viana (1980), Bahadur, Ashrafuzzaman, Chowdhury & Shahidullah, 1999; Palle & Lauer (2002). Maize variety SC401 (early maturing) was chosen as a coping strategy to rainfall variability that characterise sub-Saharan Africa

The effects of the independent variables fertiliser, soil conditions and weeding are tested using a range of treatments (Table 1) across different rainfall seasons. The ranges are chosen to enable comparisons. Fertiliser ranges between 0 (no fertilizer) to 100 kg/ha (based on an average taken from other studies of high fertiliser usage) (Bello, Afolabi, Ige, Abdulmaliq, Azeez & Mahmud, 2012; Adesoji, Abubakar & Labe, 2013). Weeding ranges from no weeding to optimal weeding (Table 1), found in previous studies (Abouziena, El-Karmany, Singh & Sharma, 2007; Masere, 2011) and based on our own simulation results. Three soil types are chosen based on Plant Available Water Capacity (PAWC) which is important for crop productivity. APSIM provides a module that simulates different soil PAWC types and 309, 151 and 86 are chosen to represent optimal, average and poor PAWC appropriately (Keating et al., 2003).

In reality crops and weeds grow and compete with each other for water, radiation and nutrients daily. For this reason a template provided by APSIM (Continuous Maize and Weeds) was selected that mimics daily competition (Table 1).

Table 1. Input data used to run APSIM simulations to test different treatments on maize yield

Item	Description
Simulation template	*Continuous Maize and Weeds* (APSIM version 7.4)
Climate/met files	Pietermaritzburg, from (1/10/2000 to 31/6/2013).
Soil treatments	Three soils conditions namely; best, average and poor conditions with PAWC of 309, 151 and 86 respectively.
Weeding treatments	No weeding and optimal weeding. For optimal weeding - weeding was set to occur after the weed biomass reached a maximum of 1000kg/ha with the maximum number of in crop weeding times set at 3.
Fertiliser treatments	No fertiliser (0kgN/ha), average fertiliser (50kgN/ha) and high fertiliser (100kgN/ha). Thirty percent (30%) of the total nitrogen amount (for both the 50kgN/ha and 100kgN/ha treatment) was applied at sowing using Compound D fertiliser with NPK ratio of 7:14:7. Seventy percent (70%) of the nitrogen amount was applied at five weeks after sowing using Ammonium Nitrate (34.5%N).
Planting date	25th of October every season.
Maize variety	SC401, an early maturing variety (Applied for all simulations).
Sowing density (plants per m^2)	4.7 (Applied for all simulations).

Pietermaritzburg is located at latitude 29°37′00″ S and longitude 30°22′59″ E, in eastern South African, approximately 80 km from the sea at an altitude of 596 metres above sea level. The climate of Pietermaritzburg was used because it locally represents a semi-arid environment with small scale farmers not unusual to much of sub-Saharan Africa. High rainfall variability is also a feature of sub-Saharan Africa (Reason, Landman & Tenant, 2006) and the 12 seasons of Pietermaritzburg (Table 2) used in the simulations cover a wide range.

Table 2.   Pietermaritzburg seasonal rainfall data for 12 seasons

Season	Total seasonal rainfall (mm)	Nature of season
Oct 2000 – March 2001	605.3	Normal
Oct 2001 – March 2002	322.5	Below normal
Oct 2002 – March 2003	385.1	Below normal
Oct 2003 – March 2004	410.4	Below normal
Oct 2004 – March 2005	910.3	Above normal
Oct 2005 – March 2006	403.1	Below normal
Oct 2006 – March 2007	513.6	Normal
Oct 2007 – March 2008	623.8	Normal
Oct 2008 – March 2009	560.8	Normal
Oct 2009 – March 2010	581.1	Normal
Oct 2010 – March 2011	312.0	Below normal
Oct 2011 – March 2012	448.5	Below normal

3.   RESULTS
3.1   QUALITATIVE RESULTS

Models take into account specific amounts of heat energy and water that cannot be accurately predicted in advance as it is season dependant. Simulated yields will vary due to energy and water differences but this variability will be fixed according to the actual inputs.   The optimum planting date for a particular season may not be optimal for the next seasons due to the variations in weather patterns between seasons (Prasad *et al*., 1996; Kgasago, 2006). Thus, we suggest that planting date is not easily predicted using simulation. Possible ranges in yield variability due to variable weather needs to be provided by simulations. However, the best planting date has to be estimated as well as possible in advance based on the best possible knowledge through farming experience and indigenous knowledge. Examples of this type of informed knowledge include using the date and quantity of the first rains (Prasad *et al*., 1996; Masere, 2011).

As long as sowing density is within a fairly broad range (3 – 9 plants per square metre) this has little effect on yields (Medeiros & Viana, 1980; Bahadur *et al*., 1999; Palle & Lauer, 2002; Abuzar, Sadozai, Baloch, Baloch, Shah, Javaid & Hussain*,* 2011). Thus, we have taken sowing density within this range. This factor is also directly related to row and in-row spacing. The best maize variety is generally region specific and known to the farmers and extension officers. These decisions are based on a number of factors developed by plant breeding experts.

Thus, planting date, maize variety, and sowing density were not investigated further as they are better predicted by the farmer, or extension personnel, where computer resources and expertise are stretched.

3.2   QUANTITATIVE RESULTS

The effect of weeding was considered by comparing simulations with no weeding and optimal weeding (Figures 1-4). For average and poor soil types, at any of the fertiliser levels, no weeding results in very poor simulated yields (most values are zero). Even for the optimal soils no weeding results in low simulated yields (Figure 1).   In fact with above normal rainfall (defined here as 625 mm), no weeding results in no successful yields (Figure 1).

Moreover, the results are unpredictable when there is no weeding (Figure 1), especially as compared to optimal weeding (Figures 2-4). With no weeding the same fertiliser and rainfall result in poor yields or very different yields.
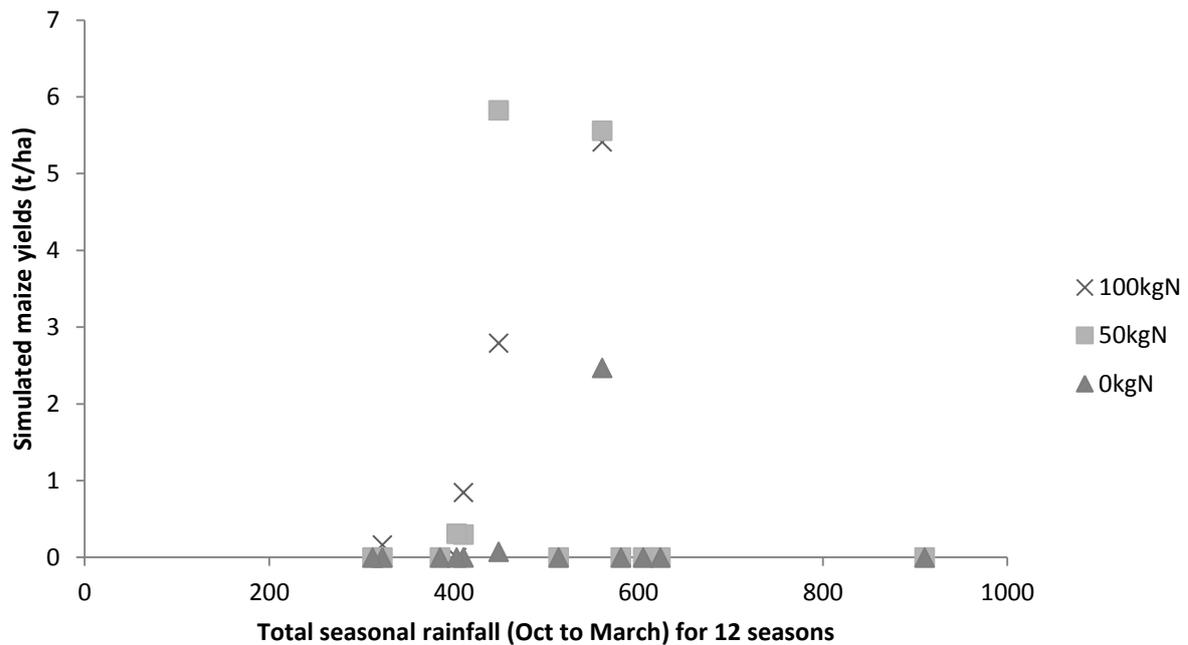

Figure 1.   Simulated maize yield response to three fertiliser levels under optimal soil conditions with no weeding for 12 seasons

Due to the fact that no weeding leads to poor or unpredictable yields, further results use optimal weeding conditions.

The importance of soil conditions on maize yield was considered by simulating the same treatments over three different soil conditions. Optimal soil conditions generally result in better yields, the better the soil condition the better the yield (Figures 2-4).

For optimal soil conditions fertiliser has a clear effect on simulated yields (Figure 1). Regardless of rainfall, zero fertilizer results in poor yields, average fertilizer results in average yields and optimal fertiliser results in the best overall yields. In particular, for optimal soil conditions any fertilizer clearly improves yields. For average and poor soils the relationship is more dependent on rainfall (Figures 3 and 4).
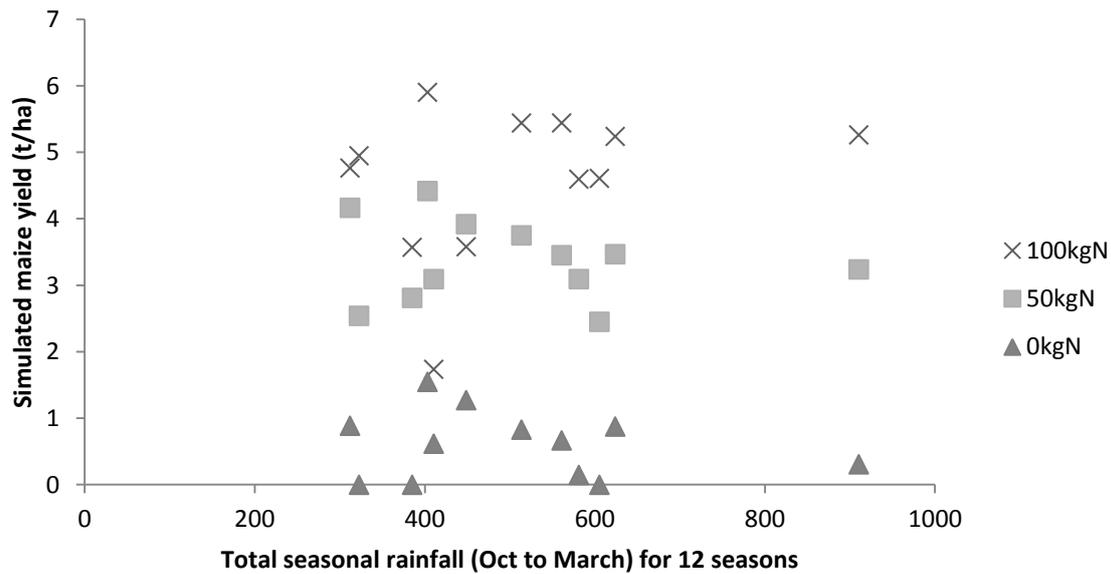
Optimal soil conditions

Figure 2. **Simulated maize yield response to three fertiliser levels under optimal soil conditions for 12 seasons**

For poor soil conditions, average fertiliser used in normal and below normal rainfall seasons (less than 625mm) results in best overall simulated yields (Figure 4). For average soil conditions, average fertiliser also performs well in normal and below rainfall seasons (Figure 3). Conversely in an above normal rainfall season the yield-fertiliser relationship for average and poor soils mimic that for optimal soil conditions where yield increases proportionally with fertiliser amount (Figures 3 and 4).
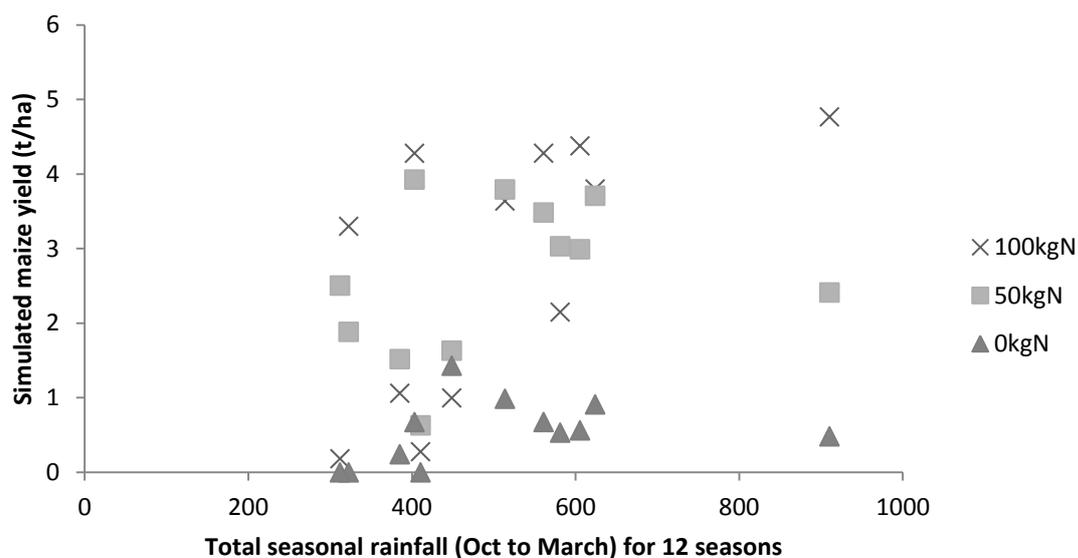
Average soil conditions

Figure 3. **Simulated maize yield response to three fertiliser levels under average soil conditions for 12 seasons**
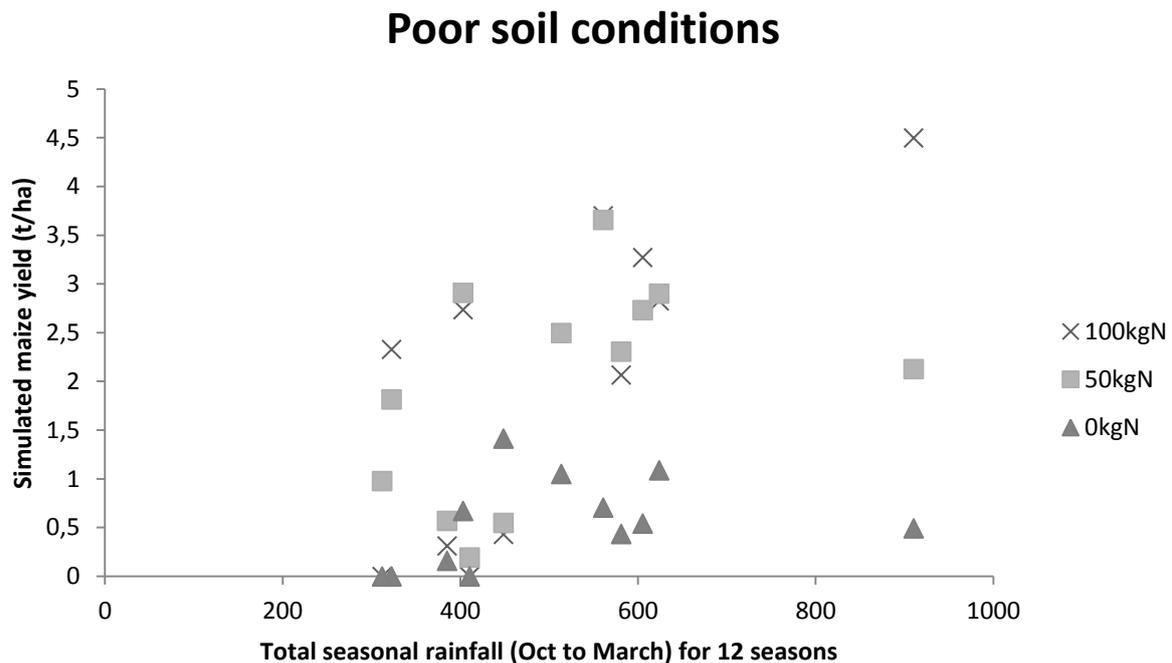
Poor soil conditions

Figure 4. Simulated maize yield response to three fertiliser levels under poor soil conditions for 12 seasons

4.   DISCUSSION AND CONCLUSIONS

Important management factors, namely planting date, sowing density, maize variety, weeding, soils and fertiliser were considered and are discussed and evaluated based on whether they benefit from model simulations in providing information for farmers to optimise crop yields. For those factors that a model might be less useful for the farmers can draw on their own indigenous knowledge and experience. These results were considered from the perspective of small scale farmers with limited computer resources and expertise.

Planting date, while important, is probably best estimated through farming experience and indigenous knowledge. It is less likely to benefit from simulations because actual seasons will vary regardless of the date chosen. Experience in predicting a particular season's weather must be relied on. Often this is based on the date and quantity of the first rains. Sowing density has been shown previously to be optimal in a fairly broad range and can be predicted by farmers and extension personnel experience or knowledge. Knowledge of the best varieties will depend on the region and is also usually known. Thus, we suggest that planting date, maize variety, and sowing are better predicted by the farmer, or extension personnel, where computer resources and expertise are stretched. Other sources of information can also be used such as books and magazines.

It is generally accepted that weeding is crucial if significant yields are to be realised. In particular, weeds growing in maize crop fields reduce maize yields through yield-attributing parameters (Abouziena *et al*., 2007). What is interesting is that our simulations indicate that weeding affects risk as well. For above normal rainfall and no weeding simulations predict no yields and for below normal rains simulations results are highly variable. These results are

confirmed by actual maize crops (a similar variety) which produced no yields without weeding (Rao, Shetty, Reddy & Sharma, 1987).

Thus, our results indicated the importance of weeding. Small scale farmers through their indigenous knowledge and farming experiences must weed their fields optimally regardless of rainfall, fertiliser amount used and soil type (Abouziena *et al.,* 2007; Masere, 2011). Small scale African semi-arid farmers usually weed their fields at least twice using a hand-hoe and base their weeding decisions on weed pressure (Masere, 2011). Similar findings were noted in a study by Abouziena *et al*. (2007). However, in that study there were no significant differences between hand-hoeing twice or three times in controlling weeds, thus two weeding sessions can be optimal.

Based on our findings it does not appear to be necessary to involve model simulations in weeding decisions because regardless of other factors no weeding increases the risk of low yields. Weeding can be optimised using informed knowledge and is a lower cost investment compared to other management factors like fertiliser investment. Most small scale farmers provide their own labour for this operation and do not place a monetary value to their effort (Masere, 2011). Thus they can weed their fields as necessary to achieve optimal yields. Thus, weeding and planting date are variables that the farmer must control using existing knowledge and experience. This consequence on the decision management process is important as it simplifies the technical aspects of the prediction process and saves money. However, where farmers are less informed of the importance of these factors the processes involved must be passed on to them through extension and other education.

Soil conditions are an important aspect of farming as they determine the crops suitable to grow and also offer a platform for the interaction of fertiliser, crops and water. Thus soil conditions have a bearing on yields. Small scale farmers are usually located in areas with poor soils and thus get poor yield returns (Mashiringwani, 1983; Masere, 2011). This is made worse by the fact that most of these farmers do not apply fertiliser to improve yields. Rohrbach and Okwach (1997) noted that only 5% of small scale farmers in southern Zimbabwe were using fertilizer. Although farmers do not have much control of soil conditions it is important for them to know how to manage them in order to get the most of out of them.

With weeding and planting date now left to tried and tested practices, fertiliser remains as the management variable that model simulations might help in determining yield predictions. Nitrogen is known to be the most limiting nutrient in crop production in most parts of the world (Fageria & Baligar, 2005). Further, the nitrogen in fertilisers is primarily responsible for high maize yields (Adesoji *et al*., 2013). However, the most crucial determinant of yield as noted by Masere (2011) and also shown here is the interaction between fertiliser and rainfall particularly for average and poor soil conditions.

Fertiliser has a clear impact in optimal soil conditions for all the rainfall conditions tested. Applying fertiliser improves yields. In average or poor soil conditions and normal (or less) rainfall, fertilizer also improves yields (there are a few exceptions). In these soils with above normal rains optimal fertiliser produces optimal yields as in the case of optimal soils. Thus, in optimal soil conditions, or when there are above normal rains, optimal yields are produced by maximising fertiliser. However, the relationship between soil, rain and fertiliser is more subtle in other conditions and this is where predictive models will be helpful.

Situations where lower fertiliser levels result in better simulated yields, as compared to greater levels of fertiliser, were also reported in a study by Masere (2011). Here both APSIM and on-farm experiments showed that better yields can be obtained when a lower level of fertiliser were used than when higher fertiliser levels were used in below normal rainfall seasons and poor soils. This justifies why most small farmers in semi-arid environments with poor soils are sceptical in applying fertiliser in below normal rainfall seasons (Rohrbach & Okwach, 1997; Masere, 2011). However, there are other reasons for the low percentage of small scale farmers using fertiliser including that it is expensive; it is not readily available and lack of credit facilities for the resource constrained poor farmers (Rohrbach & Okwach, 1997; Adesoji et al., 2013). This low fertiliser usage rate is not only prevalent in Zimbabwe, but throughout Sub-Saharan Africa and Africa with an average use rate of 8kg/ha and 20kg/ha respectively against the world average application rate of 93kg/ha (Roy, 2007).

It would appear that improving yield predictions using computer models could be beneficial for two reasons. First, there is a clear potential improvement in using fertiliser. Second, this potential improvement is combined with risk involved due to potentially yield variability and costs of fertiliser. For example, assume that a farmer has a field with average soil conditions and normal rains are predicted. Simulations for average soils and rains varying from 400 mm to 600 mm all predict that 50 kg of nitrogen per hectare will suffice to improve yields significantly. In fact, a further cost benefit analysis could further demonstrate this potential. For example, a farmer obtains 4.279t/ha and 3.926t/ha using 100kgN/ha and 50kgN/ha in a 403mm seasonal rainfall. This gives a net yield gain of 0.35t/ha after investing in an additional 50kgN/ha. However the cost of fertiliser needed to achieve a 50kgN/ha is R900 and the producer price for maize is R2500/ton implying that a farmer will get an additional income of R875 for the extra R900 invested in additional 50kgN/ha fertiliser. Using 50kgN/ha for rains between 400mm and 600m will result in an average yield of 2.745t/ha compared to 2.604t/ha obtained when 100kgN/ha is used. This means for every Rand invested in fertiliser the return is R7.63 and R3.62 when 100kgN/ha and 50kgN/ha are used, respectively. Also, keeping in mind that our simulations are illustrative and actual simulations can be more specific.

Any software solution could be useful. However, APSIM is a well-researched package and has been extensively tested (Dimes et al., 2003; Keating et al., 2003; Carberry et al., 2004; Probert & Dimes, 2004). In fact, no other program has more test sites in Africa (Keating et al., 2003). It is freely available; however, using it takes a certain degree of sophistication and learning to use it effectively takes invested time and money. In much of Africa where small scale farmers are less likely to have been afforded the necessary skills this creates a problem (Struif-Bontkes & Wopereis, 2003). The study proposes that more simplified and user friendly systems be developed to assist with this problem. Either, different simpler software be developed or a simple front end to programs like APSIM be developed. These technologies can then be provided to extension offices for helping farmers make crucial management decisions. The results highlight the factors that need to be focussed on in developing these technologies.

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