Adjustment of nitrogen inputs in response to a seasonal forecast in a region of high climatic risk

B.A. KEATING[1], R.L. McCOWN[2] and B.M. WAFULA[3]

[1] *CSIRO, Division of Tropical Crops and Pastures, 306 Carmody Rd St Lucia, 4067 Australia*
[2] *Agricultural Production Systems Research Unit, P.O. Box 102 Toowoomba, Queensland, 4350 Australia*
[3] *Kenyan Agricultural Research Institute, P.O. Box 340 Machakos, Kenya*

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Abstract

Responses to inputs such as nitrogen (N) fertilizer can vary dramatically from one season to the next in association with the rainfall variability in semi-arid climates. Traditional agricultural experimentation has examined fixed strategies of fertilizer management, but farmers frequently make tactical adjustments to their management in the light of what they perceive as information relevant to the prospects for the forthcoming crop. In this paper, we use a crop simulation model to examine the value of changing N fertilizer application rates in line with predictions of likely response to fertilizer based on the date of season onset. The analysis, using the CERES-Maize model, is centred on maize production in Machakos, a semi-arid district in eastern Kenya.

The timing of sowing relative to defined onset criteria was examined, and the value of minimizing delays in sowing after onset quantified. Assuming sowing takes place at onset, a set strategy based on 45 kg N ha^{-1} maximizes returns, but nil or negative returns were associated with N fertilizer inputs in 40 % of seasons.

The date of season onset was found to be a useful predictor of response to fertilizer inputs. A conditional strategy in which N fertilizer application was adjusted in relation to onset-date, resulted in only a small increase in expected gross margin. As far as production was concerned, the use of some fertilizer, irrespective of seasonal outlook, was the highest priority.

The impact of tactical adjustments in fertilizer use on the associated risks were assessed using a number of criteria. The results indicate that conditional strategies reduced the risk of negative gross margin and may be valued by extremely risk-averse farmers contemplating fertilizer use.

Introduction

Agricultural experimentation has traditionally compared farming strategies consisting of actions that are fixed over time. The yield of one cultivar is compared with another; one planting date against another; different rates of fertilizer are used in an attempt to find an optimum, and so on. While farmers may have a relatively fixed domain within which they operate, many of the decisions they make are conditional in nature. Their strategies of farming include many decision nodes in a decision tree from which various actions arise. The majority of decisions are made in the light of additional information in the form of current or preceding seasonal, management or economic events or states. The term "tactics" has been used to describe opportunistic changes to a

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general strategy to take advantage of short-term conditions (Connor and Loomis 1991). In the more general context of decision theory, tactics represent choices from the set of possible actions that are available at decision nodes in the decision tree. A fixed strategy is a special and simpler case of the general decision problem–that is one in which there is no possibility of obtaining further information (Anderson et al. 1977). While there is no theoretical need for such a distinction, we refer to set strategies ($S_{1\ to\ n}$) and conditional strategies ($C_{1\ to\ n}$) as we examine prospects for nitrogen fertilizer use in this paper.

Research on conditional strategies has been constrained by methodological problems. Such strategies assume greatest importance in climates of high variability and field experiments would need to run for a large number of years to adequately sample this variability. Traditionally, uncontrolled climatic variation has been lumped with all other uncontrolled variables. Advances in the simulation of crop growth hold promise for both the design and evaluation of farming strategies in which management decisions are conditional on other events or states. The assessment of a wide range of both set and conditional management practices over long periods of historical weather information through crop or cropping system models is possibly the only realistic means by which they could be evaluated.

Classes of forecast

Application of a tactic to farm management requires that some information or forecast relevant to the prospects of a forthcoming crop is available at a time when the farmer still has the chance of responding with revised management actions. This information can be directly relevant to a forthcoming crop (e.g. soil water at sowing) or be a adequate surrogate for such information (e.g. rainfall over a fallow period).

Some examples of information sources upon which forecasts have been based include:

- Climate information e.g. onset date of rains, rainfall quantities (Stewart and Faught 1984), long term weather forecasts such as the Southern Oscillation Index (Hammer et al. 1991).
- Soil information e.g. soil water content in relation to decisions on fallowing (Fischer and Armstrong 1987).
- Past crop or fertilizer management history.
- Current crop performance e.g. tissue analysis, sap tests, tiller number in relation to within-season decision making on the need for additional nitrogen fertilizer in wheat (Van Herwaarden et al. 1989).
- Past crop performance e.g. past grain protein levels in relation to decisions on nitrogen fertilization of wheat (Woodruff 1987).

Conditional strategies in traditional farming systems

The generalised notion of the decision problem, with one or more sources of information on system state providing forecasts of future system performance, is equally applicable to intensive agricultural production and to traditional subsistence farming systems. This paper is focused on the latter and our views have been strongly shaped by experiences gained in working with the predominantly subsistence farmers of a semi-arid region in eastern Kenya. In such systems, farmers have a range of tactics available to them as a season unfolds, and their perceptions of its quality develop (O'Leary 1984). Many farmers attempt to have at least a portion of their crop land planted to maize before the rains commence. The rate at which planting proceeds on the remaining land will be influenced by the timing and intensity of the opening rains (Ockwell et al. 1991). If the rains start late and, in the farmer's mind, do not hold promise for a good season, farmers will start to plant more drought tolerant crops like sorghum.

Objective of this paper

A strategy for making nitrogen fertilizer application conditional on the timing and extent of the early seasonal rains had been proposed for a region in semi-arid eastern Kenya by Stewart and Faught (1984). This was referred to as "Response Farming" and the details of the scheme have been evaluated by Wafula (1989) and McCown et al. (1991). In the current paper, we revisit response farming, but only insofar as it provides an example of a conditional management strategy. Much of the detail previously covered will not be repeated. Instead, we shall focus on the potential for simulation to assess conditional strategies of crop management.

This paper outlines the modeling approach employed and the work needed to develop a capability to realistically simulate conditional management strategies. In this region, farmers plant largely in response to what they consider to be the onset of the rainy season. This varies greatly from year to year. Hence, we initially examine simulations with plantings made at 'onset', and for various delays after onset, to identify an optimum planting strategy. The general prospects for nitrogen fertilizer use in the region are examined in terms of set strategies, and then the benefits of conditional strategies with fertilizer inputs linked to forecasts of season potential are assessed.

Methods for evaluating strategies for N management

The work was conducted in a semi-arid region of eastern Kenya where maize is the staple crop. The bi-modal rainfall regime allows two crops to be sown each year, but the risks of drought are high with rainfall less than 250 mm expected in 40 % of seasons. Little fertilizer is used (Rukandema 1984) and when adequate rain is received, yields generally remain low because of N deficiency (Jaetzold and Schmidt 1983).

Rapid population growth and degrading land resources in this region have created intense interest in more productive farming systems (Lynam 1978; Lele 1989). The high risk of poor returns to fertilizer inputs in drought years is often quoted as major deterrents to their use. Our analysis (Keating et al. 1991; McCown and Keating 1992) supports the view expounded by Ruthenberg (1980) that productive systems are unlikely to be achieved in such situations without a major injection of nutrients in the form of mineral fertilizers.

Model development and performance

The CERES-Maize model (Jones and Kiniry 1986) was chosen as an appropriate model. This model dealt with the major N transformations in the soil and the important crop growth and development processes in response to environment and management. The input requirements of the model were feasible in our situation.

We commenced this work with version 1 of CERES-Maize in 1985. The model was extensively evaluated at a number of sites in semi-arid eastern Kenya over the period 1985 to 1989. While performance of the original model was reasonable, a number of revisions were made to deal with problems encountered during its application in Kenya. In addition, a number of enhancements were made to allow for more realistic simulation of both fixed and tactical management options (Keating et al. 1991).

The severity of the water deficits encountered in the region under study were so great that crops actually died. The original model would not simulate crop death, but allowed severely stressed crops to remain in 'suspended animation'. If rain was received later in the vegetative growth period, the simulated crops recommenced growth and low, but significant, yields could be achieved. In reality, such crops were dead and the farmer would have considered re-sowing on the late rain. Routines were introduced which killed crops in response to an accumulated index of water deficit during the early- to mid-vegetative growth period.

Silking was found to be delayed by severe water or nitrogen stress, and changes were made to the model to simulate such delays. A number of other changes were made which we felt improved model integrity or had conceptual advantages. Some of these changes have also been addressed in version 2 of CERES-Maize.

Planting date was an input in the original model, fixed for any particular crop being simulated. This was unrealistic in this region where farmers plant in response to what they perceive as the onset of the rainy season. Routines were introduced which allow the user to define criteria for season onset in terms of the length, pattern and quantity of rain needed to initiate a planting opportunity. Related routines allow for replant options should a crop emerge, but fail to survive during an onset window.

Management information such as plant population and fertilizer rate were also fixed inputs for a particular crop being simulated in the original model. Enhancements were made which allowed these inputs to be conditional on the timing of onset of the season. For instance, if the rains started and sowing took place before a nominated date, high plant populations and fertilizer N could be set. If the rains started late, the simulation could be set up to use low plant populations and not apply fertilizer. Opportunities were also made for within-season management (fertilizer side-dressings, thinning) to be conditional on the timing and quantity of early-season rain.

The model validation dataset contained information from 159 crop/treatment combinations, with yields ranging from 0 to 8000 kg ha^{-1} in response to variation in sowing date, water, nitrogen, plant population and climatic conditions. The root mean squared deviation between predicted and observed grain yield was 689 kg ha^{-1}. The line of best fit was close to the 1:1 line (slope (s.e.) = 0.94 (0.03) and intercept (s.e.) = 249 (103)) and coefficient of determination (r^2) was 0.88. Further information on model performance is given by Keating et al. (1991).

Standard methods and assumptions for this paper

The standard inputs used and assumptions made throughout the simulation study have been described in detail elsewhere (Keating et al. 1991; McCown et al. 1991). Briefly, all simulations were conducted using daily rainfall data for the National Dryland Farming Research Centre, Katumani, Machakos, Kenya (lat. 1°35' S ; long. 37°14' E ; altitude 1601 m). In general, conditions selected are those thought to be typical of current practice or recommendations. Two crops per year were simulated over the 1957 to 1988 period. The short rains (SR) occur from October to January and the long rains (LR) from March to July.

Onset of the long rains season was deemed to occur when 40 mm of rain was recorded within an 8 day period, with no more than one contiguous dry day. The onset rule for the short rains was similar but based on 30 mm instead of 40 mm. Onset periods or 'windows' were defined from calendar days 289 to 327 and 38 to 106 for the SR and LR respectively. Unless specified otherwise, sowing was assumed to take place immediately season onset was detected within the window. If onset was not detected in any particular season, the crop was assumed to have been sown into dry soil at the end of the onset window. These onset criteria are based on the agroclimatic analysis of Stewart and Faught (1984) but are to some degree arbitrary and bound to be specific to regions. Nevertheless, the concepts of planting windows and minimum rain needed to initiate planting activity are consistent with farmer behaviour in this region (Ockwell et al. 1991) and are likely to be more generally applicable.

The maize cultivar, Katumani Composite B, was simulated throughout this study. The standard soil profile assumed was that of a chromic luvisol which is typical of the region. This soil has an organic carbon content of 0.8% in the surface layer, an initial mineral-N content of 54 kg ha^{-1} and a potential available water content of 173 mm over its 130 cm depth. Each season was modelled independently of other seasons with reinitialization of input parameters at the start of the onset window.

Grain yields were used to compare alternative agronomic strategies when no major input costs were involved (e.g. study of delay in planting after onset). The performance of alternative set and conditional strategies involving different input levels (e.g. studies involving different rates of fertilizer) were

Table 1. Nitrogen fertilizer and plant population levels used in the simulation study of (a) fixed strategies, (b) tactics conditional on season onset.

Set strategy	Plant population (10^3 plants ha^{-1})	N rate (kg ha^{-1})
(a) Set strategies		
S_1	22	0
S_2	27	15
S_3	33	30
S_4	37	45
S_5	44	60
S_6	55	80

Strategy	Predictor (z_i) onset date	Plant population (10^3 plants ha^{-1})	N rate (kg ha^{-1})
(b) Conditional strategies			
C_1-medium	Early	33	30
inputs	Late	33	0
C_2-high	Early	44	60
inputs	Late	33	30

compared using gross margin per hectare. The assumptions made in terms of prices of inputs and outputs are given in McCown et al. (1991). Monetary values are in Kenyan shillings (Kshs) and as a guide, 100 Kshs is equivalent to four US dollars.

Variable costs included seed, fertilizer (30 Kshs kg^{-1} N) and harvest costs. The price assumed for nitrogen is twice the purchase price to allow for variable costs of transport, application and additional weeding costs. A constant sale price of 3 Kshs kg^{-1} for maize grain was assumed.

Strategies examined

In this study, sowing was assumed to take place at onset or to be delayed by periods of up to 25 days from onset. The analysis was conducted with moderate levels of N fertilizer and plant population (S_4 in Table 1a). Other inputs were those described earlier as standard for the simulations.

Rates of N fertilizer (ranging from 0 to 80 kg N ha^{-1}) applied at sowing as Calcium Ammonium Nitrate were examined. Other studies have shown that plant population needs to be varied to match nitrogen supply if optimum production is to be achieved (Keating et al. 1991). Hence, these N rates were combined with plant populations ranging from 22000 to 55000 plants ha^{-1} (Table 1a).

Seasonal onset date was used as the predictor of seasonal potential. Seasons in which onset occurred before 18 March (calendar day 77) and 2 November (calendar day 306) for the long rains and short rains respectively were classified as early. Seasons starting after these dates within the defined onset windows were said to be late. These definitions of early and late onset were those developed by Stewart and Faught (1984). Two levels of management were evaluated, each with its own tactics for early and late onset (Table 1b). No low input level was considered since tactics are only relevant when at least some inputs are in use. The tactics evaluated can be thought of as a reduction in N fertilizer rate and plant population when a late onset forecasts a poor season.

Conceptual framework for the analysis of tactical decision-making

The conceptual framework for the analysis of decisions based on Bayesian statistical theory is well developed (Anderson et al. 1977). Bayes theory allows the probabilities of different outcomes (states) to be calculated, conditional on other events. The notion of a conditional strategy as used in this paper is essentially the decision problem where there is the possibility of gathering further information from an 'experiment'. The concepts needed for the analysis of the situation where information is available for tactical decisions are incorporated in the equation:

$$P(\theta_i | z_k) = P(\theta_i) * P(z_k | \theta_i) / \text{Sum}\{P(\theta_i) * P(z_k | \theta_i)\}$$

Where;

$P(\theta_i | z_k)$ – The posterior probabilities of θ_i given z_k e.g. the probability of a particular state (e.g. good season) after observing a particular forecast (e.g. late start). – -Relevant to conditional strategies.

$P(\theta_i)$ – The prior probability of the state i occurring, i.e. the assessment of the state's chance of occurrence based on historical weather data. – The only probability relevant to set strategies.

$P(z_k | \theta_i)$ – The likelihood of forecast z_k given state i, e.g. the chance of observing an early start to the season (forecast) given that a good season (state) will prevail.

$P(\theta_i)*P(z_k | \theta_i)$ – The product of prior probability and likelihood is referred to as the joint probability.

θ_i – The i^{th} event or state e.g. good season vs. bad season; good response to fertilizer vs. poor response.

z_k – The k^{th} prediction or forecast arising out of an 'experiment' and providing additional information about the probabilities of the states e.g. early start to the rains, late start; soil dry at planting or fully wet at planting.

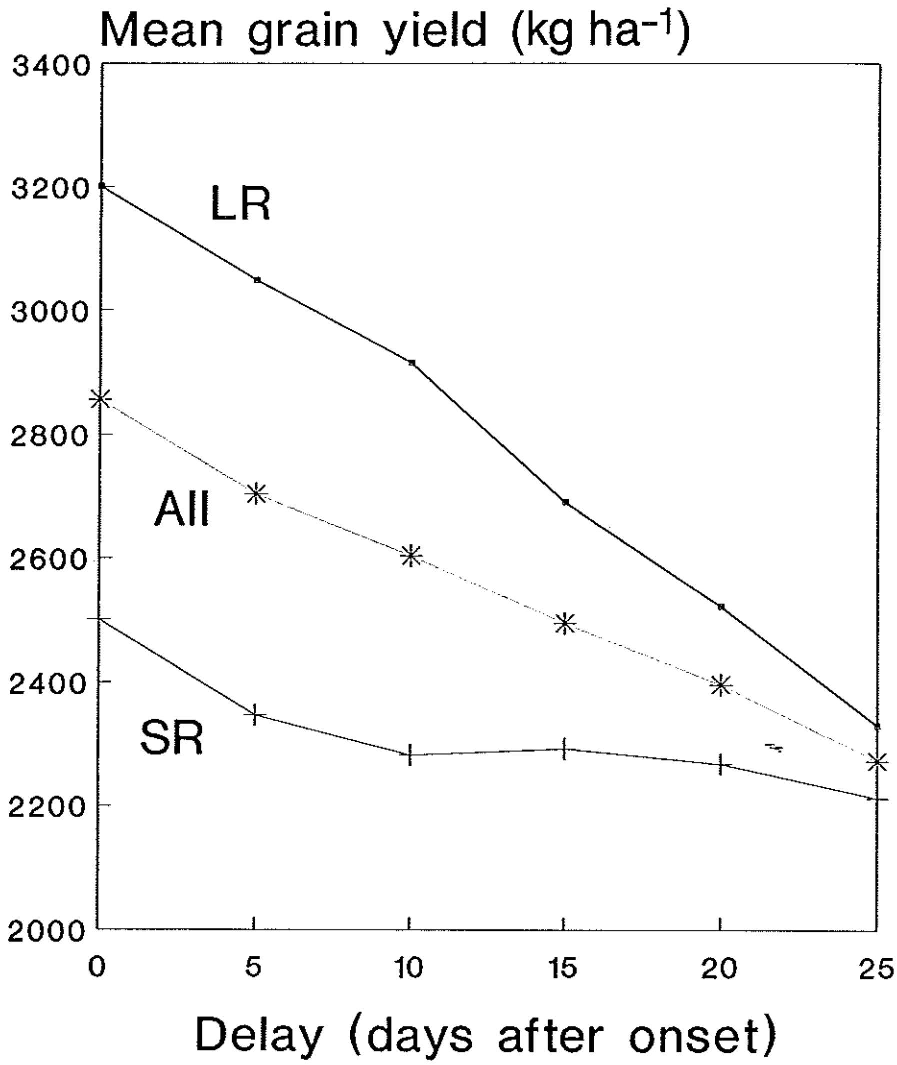

Figure 1. Effects of delay after onset in planting on the mean grain yields at Katumani in the long rains and short rains, 1957 to 1988.

Results of the simulation study

Planting strategies

It is not sensible to consider an optimal calendar date for planting in this environment, given the large variation in dates at which the seasons start. We examined the performance of crops simulated as having been planted according to some onset criteria, in comparison with crops for which some delay occurs between the time when those criteria are satisfied and planting.

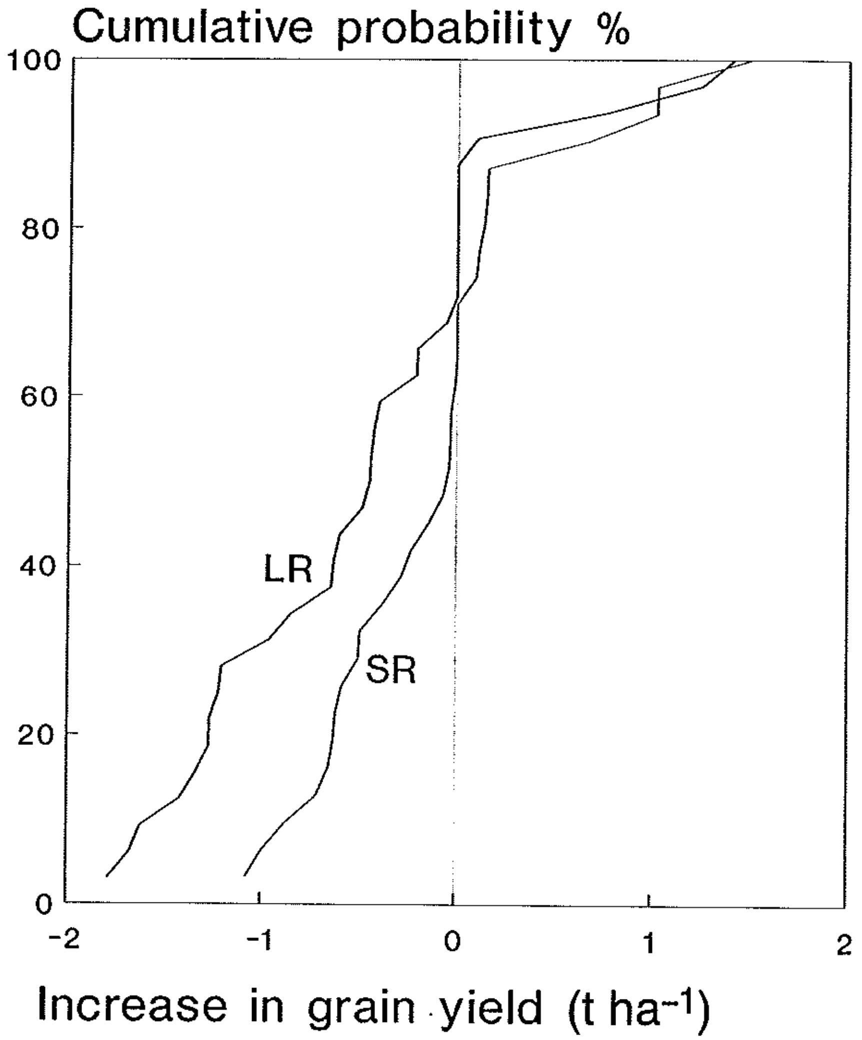

Figure 2. Cumulative distribution function for loss of grain yield associated with a 20 day delay in planting after onset for the long rains and short rains.

Mean grain yield simulated over the 63 seasons examined at Katumani declined from 2900 to 2300 kg ha^{-1} as planting was delayed 0 to 25 days after onset (Figure 1). The losses associated with delayed planting were generally greater in the long rains than in the short rains. On average, losses of 23 kg (0.8 %) of grain yield per day delay in planting were simulated over both seasons, rising to 35 kg (1.1%) per day delay in the long rains. Variation in response from season to season was great and, while losses were generally recorded, some crops benefited from delays in planting. This occurred either in situations where out-of-season rain was recorded in the January–February short dry period or

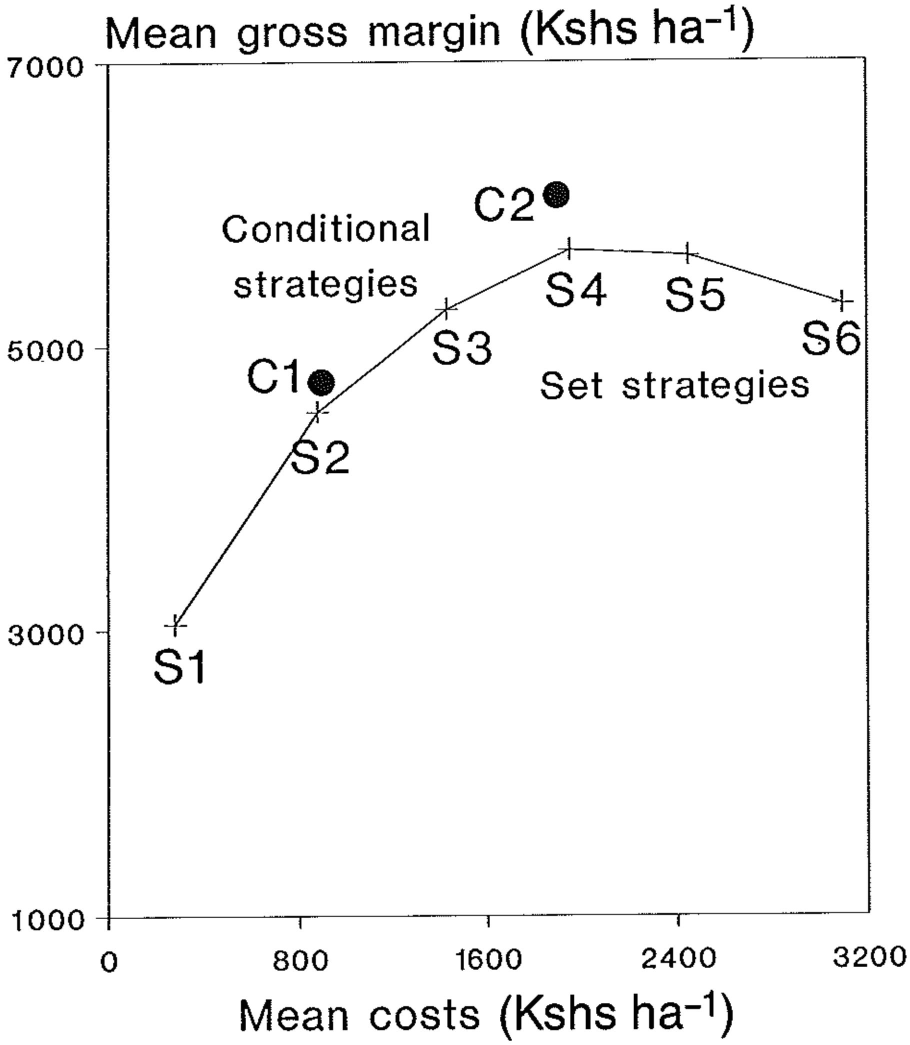

Figure 3. Average gross margin over the 1957 to 1988 period at Katumani associated with a range of fixed and conditional strategies.

when excessive nitrogen losses were limited by delayed planting in a small number of extremely wet seasons. A 20-day delay in planting after onset was estimated to lead to yield losses in 70 % of long-rains seasons and 60 % of short-rains seasons (Figure 2).

While the consequences of delays in planting will be influenced by both the definition of onset selected and interactions with other management variables such as nitrogen supply, the generally appreciated value of 'early planting' in this region is supported by this analysis (Dowker 1964). Losses associated with delays in planting can be attributed to inefficient use of both nitrogen and water

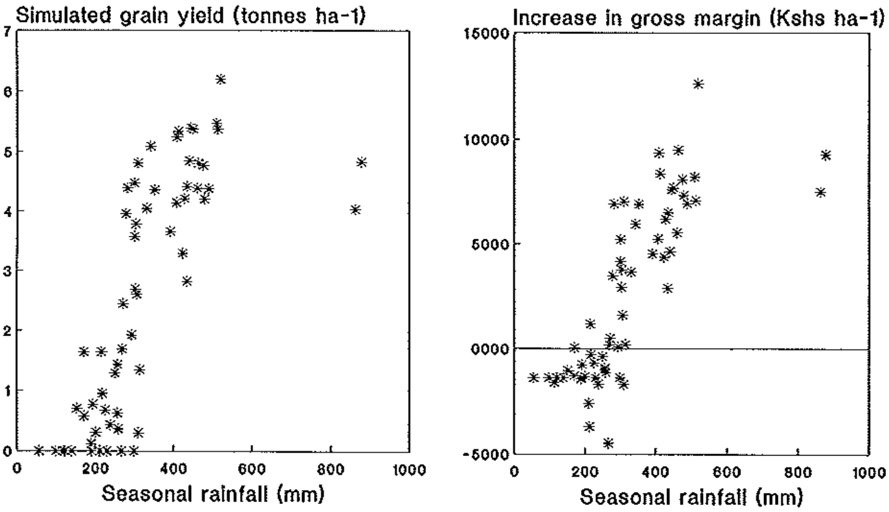

Figure 4. Relationships between seasonal rainfall (defined above) and simulated grain yield (left) and simulated response to inputs (S_4–S_1) for the long and short rains, 1957 to 1988.

resources and hence other factors which influence nitrogen and water supply or demand (e.g. fertilization, plant population, genotype) will influence the outcome of delays in planting. In the remainder of the paper, the assumption was made that planting would proceed at the optimal time, i.e. as soon after onset as possible.

Strategies of N use

Long term average grain yields increased from 1106 to 2794 kg ha^{-1} as the input level in the fixed strategies increased from S_1 to S_6. Mean gross margin were maximized (5255 to 5673 Kshs ha^{-1}) at N rates between 30 and 45 kg N ha^{-1} and plant populations between 33000 and 37000 plants ha^{-1} (S_3 and S_4 – Figure 3).

Variability in simulated response to N was extreme, ranging from positive increases in gross margin of 13000 Kshs ha^{-1} (above the crops receiving no fertilizer) in some seasons to losses of 3000 Kshs ha^{-1} associated with high rates of fertilizer use in other seasons. In general, both grain yields simulated and response to added N were strongly related to seasonal rainfall levels (Figure 4).

Tactical adjustments based on climate information

Performance of the predictor

Stewart and Faught (1984) have shown that potentially useful relationships exist in this region between the date of season onset and seasonal rainfall. McCown et al. (1991) used Bayesian statistics to update seasonal rainfall probabilities based on historical prior probabilities using a predictor (onset

Table 2. Performance of onset date as a predictor of class of response to inputs based on the comparison of S_4 with S_1 (see text for explanation of terms).

good	response>4000 Kshs ha^{-1}
poor	$0 \leq$ response ≤ 4000 Kshs ha^{-1}
negative	response<0 Kshs ha^{-1}

	Early onset							
Response	Long rains				Short rains			
to inputs	Prior	Likelihood	Joint	Posterior	Prior	Likelihood	Joint	Posterior
Good	0.47	0.73	0.34	0.74	0.32	0.80	0.26	0.53
Poor	0.22	0.14	0.03	0.06	0.20	0.50	0.10	0.20
Negative	0.31	0.30	0.09	0.20	0.48	0.27	0.13	0.27
	1.00		0.46	1.00	1.00		0.49	1.00

	Late onset							
Response	Long rains				Short rains			
to inputs	Prior	Likelihood	Joint	Posterior	Prior	Likelihood	Joint	Posterior
Good	0.47	0.27	0.13	0.24	0.32	0.20	0.06	0.12
Poor	0.22	0.86	0.20	0.36	0.20	0.50	0.10	0.20
Negative	0.31	0.70	0.22	0.40	0.48	0.73	0.35	0.69
	1.00		0.55	1.00	1.00		0.51	1.00

date). A similar approach has been taken here, except that we examined both prior and posterior probabilities of response to N inputs, rather than of seasonal rainfall. While this restricts the analysis to the N fertilization issue, it has the advantage of eliminating the scatter that we see in the relationship between response to inputs and seasonal rainfall (Figure 4). It also means that onset-date effects on factors other than rainfall, (e.g. effects on temperatures and radiation during grain filling) are captured in the analysis.

In the period studied, 47 % of long rains seasons started early, 53 % late, using the criteria outlined earlier as proposed by Stewart and Faught (1984). The likelihood of seasons with a good yield response to inputs (as assessed by the incremental yield of S_4 over S_1) starting early, is shown in Table 2. Other combinations of response and season-onset date (predictor) are also shown. Bayesian probability theory has been used to calculate posterior probabilities. For the LR, the prior probability of a good yield response to inputs is 47 % in the absence of any information concerning season onset date. The corresponding conditional or posterior probability of a good response to inputs given an early onset is 74 %. Similarly, while there was a 31 % prior probability of a poor response to inputs in the long rains, this is increased to 40 % given a late onset to the long rains.

Onset-date also changes the probabilities of obtaining responses to inputs in the short rains (Table 2). The probability of obtaining a good response to inputs is increased from 32 to 53 % if onset is known to be early. Poor responses to inputs are expected in 48 % of short rains seasons in general, but this probability is increased to 69 % if onset is late.

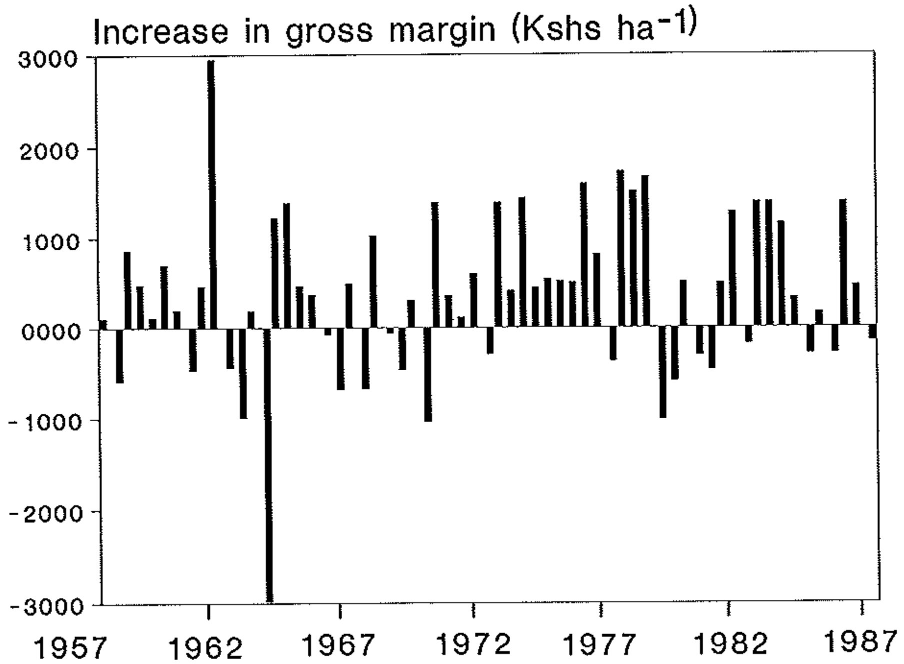

Figure 5. Variability over time of the increase in gross margin in response to conditional management (C_2 minus S_4).

It is clear that the onset-date of the rains has a major effect on the probability of obtaining a response to nitrogen fertilizer and associated inputs. A comparison of tactical management with fixed strategies considering both average returns and risks is now examined to assess the economic value of this shift in probabilities.

Average benefits

The mean gross margins for the two conditional strategies examined are compared with fixed strategies in Figure 3. For the same input cost, averaged over the period studied, tactics which link fertilizer use to onset-dates result in gains in the expected gross margin. However, the size of these gains is small in comparison with the large impact of the unconditional use of fertilizer.

Measures of risk

While the overall impact of the tactics examined on average profitability was small, reductions in the risk associated with fertilizer use also need to be assessed.

The high input conditional strategy (C_2) provided benefits over and above a comparable fixed strategy (S_4) in 67% of seasons simulated, but had a negative impact in the remainder of seasons (Figure 5). Such negative effects arose mostly (81%) from situations when an early onset was indicative of a good

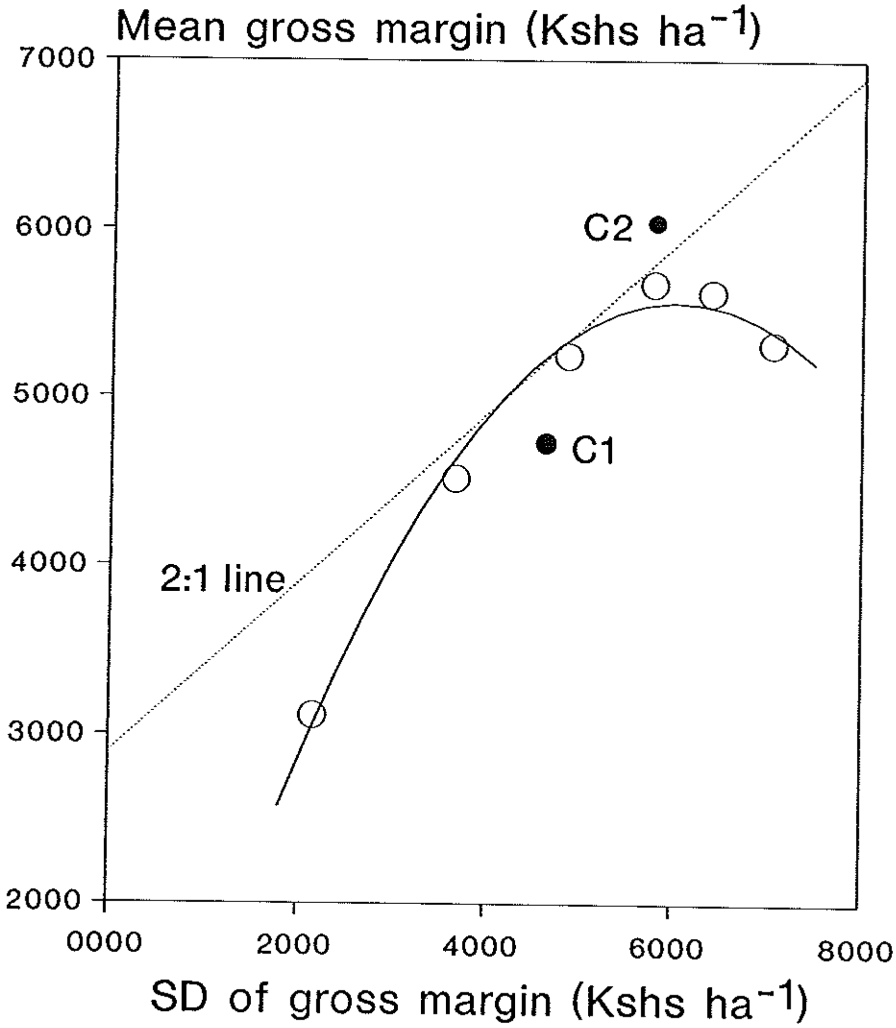

Figure 6. The outcome of various set open symbols (S_1, S_2, S_3, S_4, S_5, S_6) and conditional (C_1, C_2) strategies, specified in Table 1, plotted in mean-standard deviation space.

season and inputs were increased accordingly, but subsequent response to these additional inputs was poor.

Efficiency frontiers in Mean (E) – Standard Deviation (SD) space

McCown et al. (1991) have compared conditional strategies with fixed strategies in terms of E–SD space. The technique portrays production in terms of the long term average gross margin (E) and risk in terms of the standard deviation of gross margin (SD) over the historical period simulated (Figure 6). Compared to a corresponding set strategy (S_4), the high input conditional strategy (C_2)

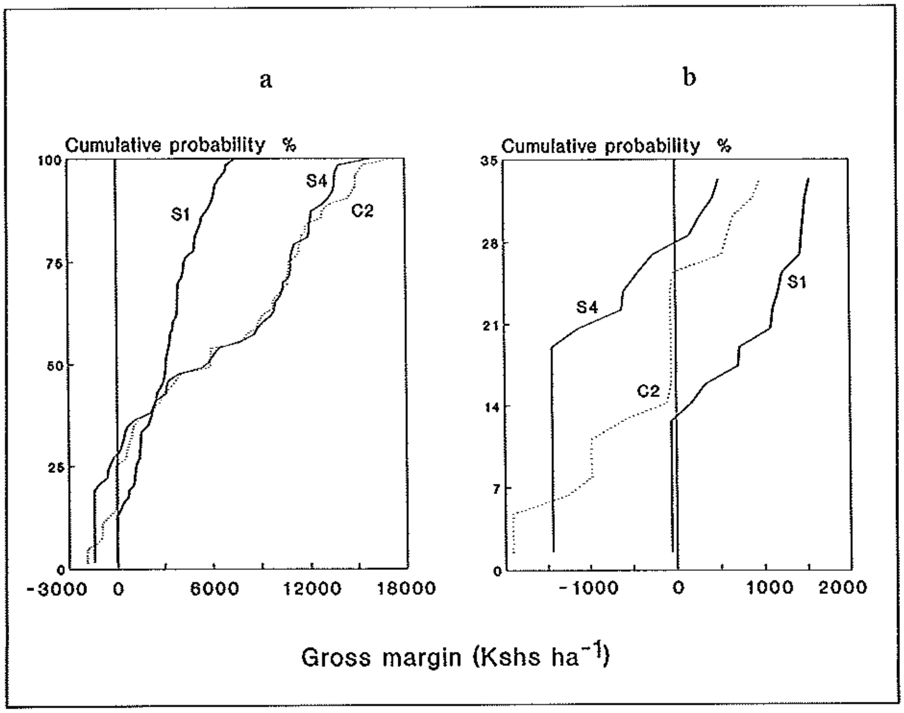

Figure 7. Cumulative probabilities of gross margin for fixed (S_1, S_4) and conditional (C_2) strategies of N fertilization. Details of strategies are given in Table 1. (a) Full range of gross margin. (b) Lower 33% of the range in gross margin.

resulted in higher mean returns with the same or slightly reduced risk, insofar as standard deviation is an adequate measure of risk. The strategy using moderate input levels conditional on onset-date (C_1) fell below the efficiency frontier generated by fixed strategies and is of no further interest. A 2:1 rule of thumb has been suggested (Ryan 1984) as a first approximation to the attitudes of farmers on small-holdings to incurring added risk in conjunction with increased gross margin, i.e. such farmers would not be averse to using inputs or technologies provided they did not increase the standard deviation of the gross margin more than twice the increase in mean gross margin. Such a rule would suggest that the S_2, S_3 and S_4 fixed strategies and the C_2 conditional strategy are realistic options for risk averse farmers. The E–SD plot also highlights the large gains in efficiency achievable through the use of inputs (S_4 vs. S_1) and conversely, the small benefits of tactics associated with their conditional use (e.g. comparing C_2 with S_4).

Stochastic dominance analysis

The cumulative distribution functions (CDF) for the gross margin (Figure 7a) compare the low-input (S_1) and high-input (S_4) fixed strategies with a high-

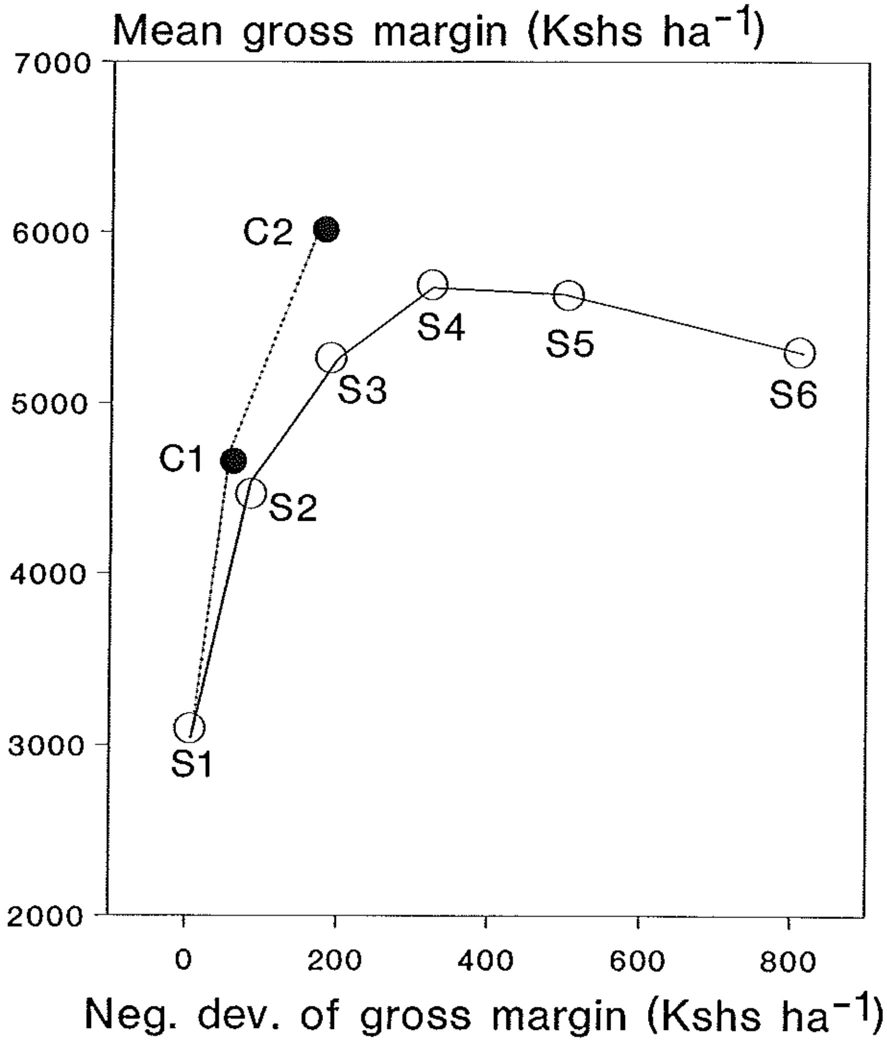

Figure 8. The value of various set (S_1, S_2, S_3, S_4, S_5, S_6) and conditional (C_1, C_2) strategies, specified in Table 1, plotted in mean-negative deviation space. The negative deviation refers to outcomes with a gross margin less than 0 Kshs ha^{-1}.

input conditional strategy (C_2). If we apply constant 'Pratt-Arrow' risk aversion coefficients (r) and stochastic dominance analysis with respect to a function (Meyer 1977; Goh et al. 1989) , the C_2 strategy dominates S_4 at all levels of risk aversion and dominates S_1 if r >0.00035. Units for r are in $Kshs^{-1}$ and the outcome space is gross margin for maize (Kshs ha^{-1}).

Stochastic dominance analysis has been used to compare risky prospects, but is limited in the absence of detailed information on farmer attitudes. We do not have an estimate of risk aversion coefficients for farmers in this region, but an earlier comparison (Keating et al. 1991) based on a study of Indian subsistence farmers (Bailey and Boisvert 1989), suggested that such a coefficient might apply to the most risk averse 8 % of farmers in that study.

A closer examination of the lower third of the probabilities for gross margin (Figure 7b) highlights the large increase in risk of a negative gross margin associated with use of fertilizer inputs (S_4 compared to S_1) and the significant reduction in this risk that was achieved with a conditional strategy using season-onset as a predictor (C_2 vs. S_4).

Safety first: Mean (E)–negative deviation (ND) space

While quantifying the production objectives of resource poor farmers is a demanding and often controversial exercise, the desire of such farmers to achieve some threshold production level needed for survival is easily envisaged. In the case of decisions concerning fertilizer inputs, the desire of farmers not to lose money (i.e. not to record a negative gross margin) can be viewed as a requirement for financial survival or 'safety-first' goal setting. Strategies can be assessed in terms of such goals by plotting the expected returns against the probability-weighted sum of deviations below some target, in this case, below a gross margin of zero (Figure 8). Such a plot in mean-negative deviation space (E–ND) (Parton, 1992) has obvious parallels to E–SD space considered earlier (Figure 6). E–SD space uses all variability in returns as an indicator of risk (i.e. deviations both up and down) while E–ND space considers only the down-side risks. While conditional strategies of fertilizer use raised expected returns slightly, it had little impact on risk as assessed in the E–SD plot (Figure 7). Tactics linked to an onset-date forecast did however have a substantial benefit in reducing negative deviations (Figure 8) and may be attractive to farmers pursuing strong 'safety first' goals.

The implicit utility function in the E–ND space as presented here is one that places a value on reducing losses that is proportional to the size of the reduction, but that places no extra value on profit over and above the target level. This is obviously an extremely risk-averse position to take, but the plot does highlight the potential attraction of conditional strategies of fertilizer use for highly risk-averse individuals.

Discussion

The date of the start of the rains at Katumani can be a useful predictor of potential yield, and hence of the capacity of crops to respond to inputs. Adjustment of N input levels and plant populations to better match the season potential is a logical response with a sound biological basis. How much value to place on the forecast is more difficult to assess. In terms of average returns, its value is small relative to the large benefits from using fertilizer irrespective of a forecast. In terms of minimisation of risks, it can be of value, substantially reducing the number of occasions when fertilizer is purchased and rainfall is insufficient to obtain a return in the year of application.

We have not considered the residual value of fertilizer applied in such situations, but other experimental (Watiki and Keating unpubl. data 1988) and simulation (Keating et al. 1991) studies suggest that it can be significant in dry years. Information concerning past fertilizer management and prior rainfall data could serve as forecasts of the likely value of residual fertilizer. Conditional strategies could be developed that adjust current fertilizer management in response to both future seasonal prospects and hence nutrient demand (as in this study), and to nutrient supply as influenced by past management and weather.

This and earlier studies in the region highlight the potential economic value of fertilizers and yet we observe few farmers using fertilizers. An analysis of possible reasons why more farmers don't use fertilizer has been given by McCown et al. (1991).

It is clear from the simulation results that anything less than 20 to 30 years would not provide an adequate picture of the variability in net benefits associated with a particular tactic. Experimental evaluation of the conditional management strategies (examined in this paper using simulation) would not have been feasible. The models we use remain fairly crude tools in the evaluation of the decisions that confront farmers. Considerable local adaptation was needed in this study to deal realistically with the crop system of interest. Some of this adaptation was of a technical nature, such as the recalibration of a function or correction of an error of logic. The most important changes in this work were, however, those that broadened the scope of the model to deal with aspects of the system we felt had to be addressed if realistic simulations were to be achieved. Changes included such issues as the ability to simulate planting in response to weather rather than as a fixed input, and the ability to simulate the death of crops severely stressed during the establishment and early periods of vegetative growth. The solutions developed on problems such as crop death were based on limited data and further research is needed. Despite the enhancements made to the model in this study, we are still working essentially with a crop model and as such, fairly inadequate tools in the assessment of matters of a cropping system or farming system nature.

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