ASSESSING THE VALUE OF A SEASONAL RAINFALL PREDICTOR TO AGRONOMIC DECISIONS: THE CASE OF RESPONSE FARMING IN KENYA

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ABSTRACT

High yields in the semiarid tropics cannot be achieved without soil fertility amendment, but there is a high risk that rainfall deficits will prevent the realisation of yield gain from higher fertility. Without a means of anticipating the "goodness" of the oncoming season, the best that a profit-seeking farmer can do is to set a crop-limited yield potential tailored for the typical season. Such a strategy unavoidably results in lost opportunities for high yield in good seasons and wasted inputs in poor seasons.

It is generally perceived that improved seasonal rainfall forecasting is needed for large gains in efficiency of input allocations. Response Farming was developed in Eastern Kenya to forecast season type using rules based on time of season onset and early cumulative rainfall. Tactical agronomic responses, such as adjustments in crop densities and nitrogen fertiliser amounts which determine the crop yield ceiling and demands on soil resources, are then possible.

Although reports on the development of Response Farming have tended to capture the imagination of scientists, there is little information that quantifies the potential value of the scheme to increase and stabilise agricultural production. Testing using a numerically simulated system is feasible, and recent research in Kenya has adapted and validated the CERES-Maize model to predict yield in response to variation in water and nitrogen supply, and for variable plant population densities. In this paper, the model is used to simulate maize yield for both long and short rainy seasons for 32 years at Katumani Research Station, near Machakos, Kenya. A range of practices and strategies are compared. These differ in the initial plant population and amount of fertiliser applied and, when a forecast is available, the timing and degree of subsequent adjustments.

A decision analysis approach was used, firstly, to compare the efficacy of two seasonal rainfall predictors in reducing uncertainty and, secondly, to compare the economic performance of various input allocation strategies with and without forecast information.

Using Bayes theorem, Response Farming forecasts were shown to substantially reduce within-season rainfall uncertainty. Economic comparisons of input strategies using expected utility and mean-standard deviation analysis showed that: (i) the low input strategy typical of small farms in the region is greatly inferior to the optimal strategies with or without a forecast; (ii) of the Response Farming strategies compared, the optimal one used the highest inputs; and (iii) Response Farming strategies using lower inputs were not superior to the optimal Set strategy. Various explanations of the suboptimality of current farming practice are explored, including possible weaknesses in the analysis.

Recognising that farmers change their practices incrementally, the results indicate that the most important step is increased use of nitrogen fertiliser irrespective of seasonal outlook.

These results demonstrate the synergy of cropping systems simulation and decision analysis methods in the pursuit of improved farm management.

INTRODUCTION

The efficiency with which land, capital, and labour are used in producing crops in semiarid climates is reduced by the high probability that the yield opportunity provided by chance rainfall in a given season will not match the yield potential set by the farmer's selection of crop, plant population, and soil fertility amendment. In unexpected dry years, variable inputs are not fully utilised by the crop and often exacerbate water deficits. In unexpected years of good water supply, opportunities for high returns are foregone. Without the ability to predict the nature of the pending season, economic benefits from yield-improving technologies in risky climates will always be less than in more reliable ones.

Scientific recognition that weather systems behave chaotically much of the time, seems not to have dampened expectations that useful seasonal forecasting is feasible. Predictors based on empirical indices derived from readily-available atmospheric measurements, such as the Southern Oscillation Index, show considerable promise for some regions (e.g. Nicholls 1986, 1991; Hammer and Muchow 1991; Clewett *et al.* 1991). An alternative approach, which relies on the empirical relationship between rainfall received early in the season and eventual total seasonal rainfall also shows promise in certain regions. The most notable example of this latter type of predictor is "Response Farming" (Stewart 1988, 1991). When implemented for a region, Response Farming provides: (a) a forecast of the potential of the pending growing season in time to influence decisions that set yield ceilings; and (b) a set of alternative recommendations for all forecast contingencies. Since publication of a Response Farming scheme for Eastern Kenya (Stewart and Hash 1982), the concept has aroused widespread interest among agricultural research and development practitioners. An institution expressly for the promotion of Response Farming has been assisting adaptation of the concepts in at least 18 countries (Stewart 1988). Response Farming appeals to scientists because the problem it addresses is important, the approach is intuitively sound, and the published data indicate that correct forecasts of season type can be made with sufficient frequency to appear to be "useful". However, the economic value of a Response Farming scheme for a given location has not been adequately assessed, and cannot be inferred from farmer behaviour because, as a scheme, it is yet to be adopted by farmers (Stewart 1991).

This paper is part of an evaluation of the Response Farming scheme developed by Stewart and co-workers for the Machakos-Kitui district in Eastern Kenya. Mean annual rainfall in this region ranges from 500 to 700 mm falling in two short growing seasons, termed locally the "long rains" and the "short rains". The farming system is characterised by production of maize and maize-pulse mixtures in both growing seasons. Under rapidly-increasing population pressure, land-use intensity of croplands approaches continuous cultivation, and one consequence is depletion of soil fertility. Although responses to nitrogen and, to a lesser extent, phosphorus are generally dramatic in good seasons, little fertiliser is used (Rukandema *et al.* 1981).

There is evidence that a major disincentive to the use of fertiliser is the high risk of low rainfall and resultant poor crop response to fertiliser (Ockwell *et al.* 1991). Reduction of this risk is central to Response Farming.

The economic value of a climatic forecast depends on: (i) the accuracy and timeliness of the forecast; and (ii) the degree of optimality of the decision made on the basis of the forecast (Krzysztofowicz 1983). In an evaluation of Response Farming in this paper, we firstly quantify the effect of specified forecasts on the degree of uncertainty faced by the farmer. We then identify the strategy that becomes optimal when such information is available, and, finally, we quantify the value of such information.

RESPONSE FARMING AS A CONCEPT

The Forecast

Fundamental to the derivation of a forecast in Response Farming is the empirical relationship between the relative earliness of a rainy season and determinants of its potential for supporting crop production, i.e. the season length and the amount of rainfall received (Fig. 1). Positive correlations have been reported for a wide range of tropical and Mediterranean locations (Stewart 1988). The apparent reason for this relationship is that the date of cessation of rainy seasons is less variable than that of onset, making season duration dependant mainly on the latter. A rule for classifying the onset of a rainy season as "early" or "late" is derived from historical rainfall records. Fig. 1 is divided into early and late segments providing rules for classification of season type (Predictor I) for both long and short rains (P_I, Table 1a).

A second predictor (P_{II}) developed in Kenya depends additionally on the cumulative amount of rainfall received early in the season. The correlation between this and the total rainfall received in the specified crop growing season depends largely on auto-correlation. As the length of the early period is extended, it represents a larger fraction of the total growing season, and hence the prediction is likely to be more accurate, but less useful. In Response Farming, the length of the early period is optimised, i.e. it is made as long as possible but early enough not to seriously affect the efficacy of tactical adjustments to crop water demand and yield potential by thinning or side dressing with fertiliser. The criteria for Predictor II are cumulative rainfall and onset type (Table 1b). Cumulative rainfall in the first 30 or 35 days gives rise to three classes of season, termed good, fair, and poor (Table 1c).

Agronomic Response Tactics

In developing and discussing Response Farming for Eastern Kenya, Stewart and Faught (1984) considered three nominal input levels, i.e."conventional" (low maize population/no fertiliser), "high" (high population/60 units of nitrogen (N) fertiliser), and a level "medium" in both plant population and N fertility. The higher levels of plant population in the present study are lower than those used by Stewart and Faught (1984) and Wafula (1989). Ours are based on the results

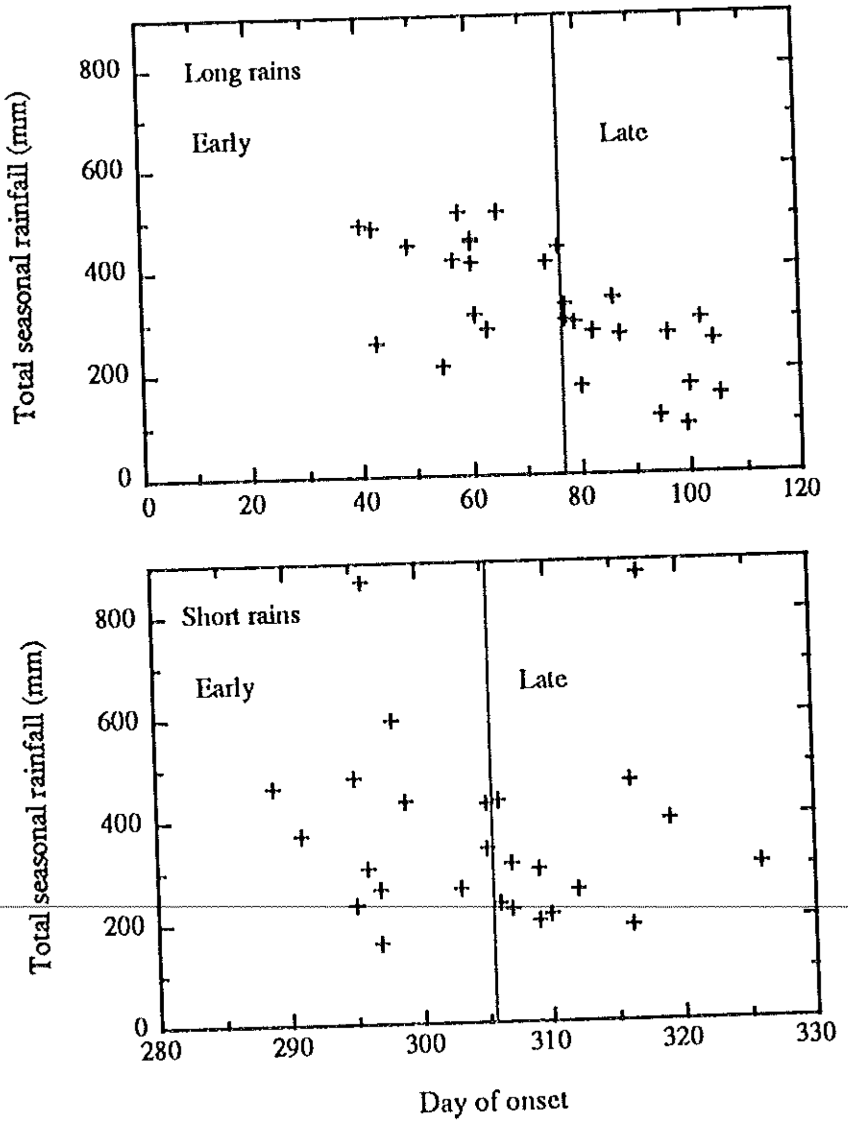

Fig. 1. The relationship between total seasonal rainfall and date of rainy season onset that provides basis for prediction. Classification into Early and Late according to Stewart and Faught (1984).

of optimising the plant population at different N levels reported by Keating *et al.* (1991).

In Response Farming, selection of levels of variable inputs is made at two stages, namely: (i) at onset of the rainy season, in response to the forecast of either good (early) or poor (late) season (Table 1a); and (ii) at 30 or 35 days after planting, in response to the forecast of type of season provided by cumulative rainfall since onset (Table 1b). In the interest of optimally matching crop yield potential with season type, options for adjusting production inputs are kept open as long as possible. Hence plant density is initially high and fertiliser

Table 1. Criteria for season type forecasts using two predictors and for classification of actual season types. Standard day is shown in parentheses. Source: Stewart and Hash (1982); Stewart and Faught (1984).

a) Predictor I (P_I) — Earliest date of receipt of 40 mm rain in 8 days+.

Onset	Season forecast	Long rains	Short rains
Early	Good	23 Jan (23) - 18 Mar (77)	16 Oct (289) - 2 Nov (306)
Late	Poor	19 Mar (78) - 16 Apr (106)	3 Nov (307) - 23 Nov (327)

b) Predictor II (P_{II})

Onset	Season forecast	Long rains: Rainfall (mm) during 35 days from onset	Short rains: Rainfall (mm) during 30 days from onset
Early	Good	> 147	> 122
	Fair	89 - 147	115 - 122
	Poor	< 89	< 115
Late	Good	> 234	> 209
	Fair	135 - 234	152 - 209
	Poor	< 135	< 152

c)

Actual season type	Rainfall (mm) between season onset and maize maturity: Long rains	Short rains
Good	> 280	> 330
Fair	150 - 280	230 - 330
Poor	< 150	< 230

+ No more than one day without rain.

input low to provide maximum flexibility for tactical adjustments to be made at the second stage decision point (Table 2c).

METHODS FOR EVALUATING RESPONSE FARMING

The first stage of the analysis concerns how well the predictors predict. The steps required are largely those in the development of a Response Farming scheme (Fig. 2). Firstly, there must be a source of historical rainfall records.

Table 2. The tactical nitgrogen fertilisation and planting/thinning responses for various Set and Response Farming strategies. P_I and P_{II} are defined in Table 1. (NC = no change)

a) Set strategies

Set strategy (S_j)	Plant population ('000s ha^{-1})	N fertiliser (kg ha^{-1})
S_1	22	0
S_2	27	15
S_3	33	30
S_4	37	45
S_5	44	60
S_6	55	80
S_7	55	70

b) Single stage Response Farming strategies using P_I

Response Farming strategy (R_j)		Plant population ('000s ha^{-1})	N fertiliser (kg ha^{-1})
R_1	High Inputs		
	z_1 (Good)	44	60 (I_H)
	z_2 (Poor)	33	30 (I_L)
R_2	Medium Inputs		
	z_1 (Good)	33	30 (I_H)
	z_2(Poor)	33	0 (I_L)

c) Two-stage Response Farming strategies using P_{II}

		Stage 1 Plant population ('000 ha^{-1})	N fertiliser (kg ha^{-1})	Forecast season type	Stage 2 Thin population ('000 ha^{-1})	N fertiliser (kg ha^{-1})
R_3	High inputs					
	z_1 (Good)	44	30 ($I_{H'}$)	w_1(Good)	NC	+30
				w_2(Fair)	-11	NC
				w_3(Poor)	-22	NC
	z_2 (Poor)	44	20 ($I_{L'}$)	w_1(Good)	NC	+40
				w_2(Fair)	-11	NC
				w_3(Poor)	-22	NC

R_4	Medium inputs z_1 (good)	33	20 ($I_{H'}$)	w_1(Good)	NC	+10
				w_2(Fair)	NC	NC
				w_3(Poor)	-11	NC
	z_2(poor)	33	0 ($I_{L'}$)	w_1(Good)	NC	+20
				w_2(Fair)	-11	NC
				w_3(Poor)	-11	NC
R_5	As for R_3 except highest pop'n 55K and N 30 + 50					
R_6	As for R_3 except pop'n 55K					

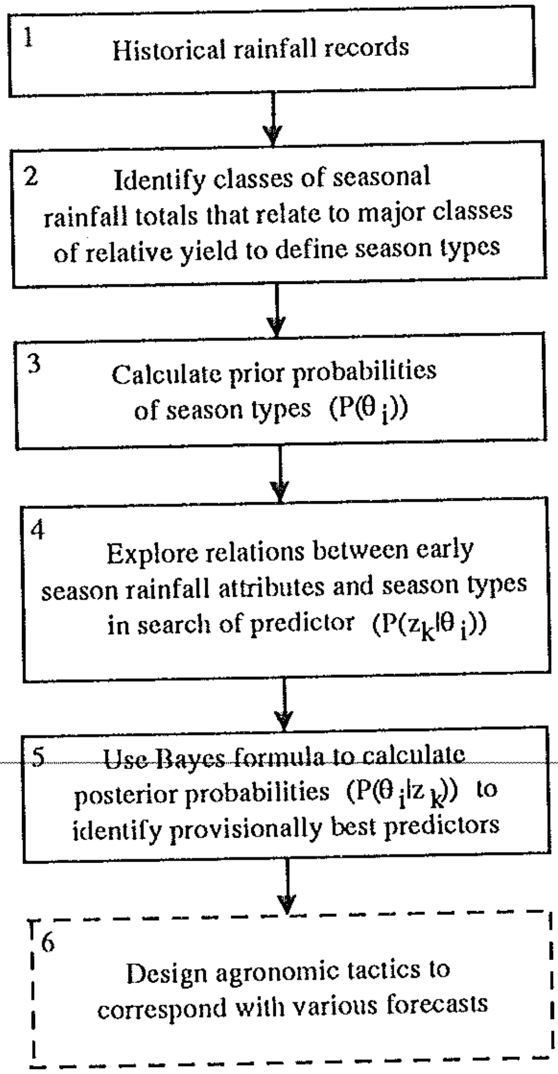

Fig. 2. Scheme for developing and evaluating a Response Farming rainfall predictor.

In this paper we use data from the Katumani Research Station, near Machakos for 1957-1988. These data were also used by Wafula (1989) and, except for the last 5 years, by Stewart and Faught (1984). Radiation and temperature data are from Wafula (1989).

Step 2 in Fig. 2 relates grain yield to seasonal rainfall. A procedure for classifying seasons in Eastern Kenya into good, fair, and poor was given in Stewart and Hash (1982) and results are presented in Table 1c. Fig. 3 shows these criteria superimposed on a plot of yield (strategy S_5, Table 2a, simulated by the model described below) and seasonal rainfall. The evaluation of predictor

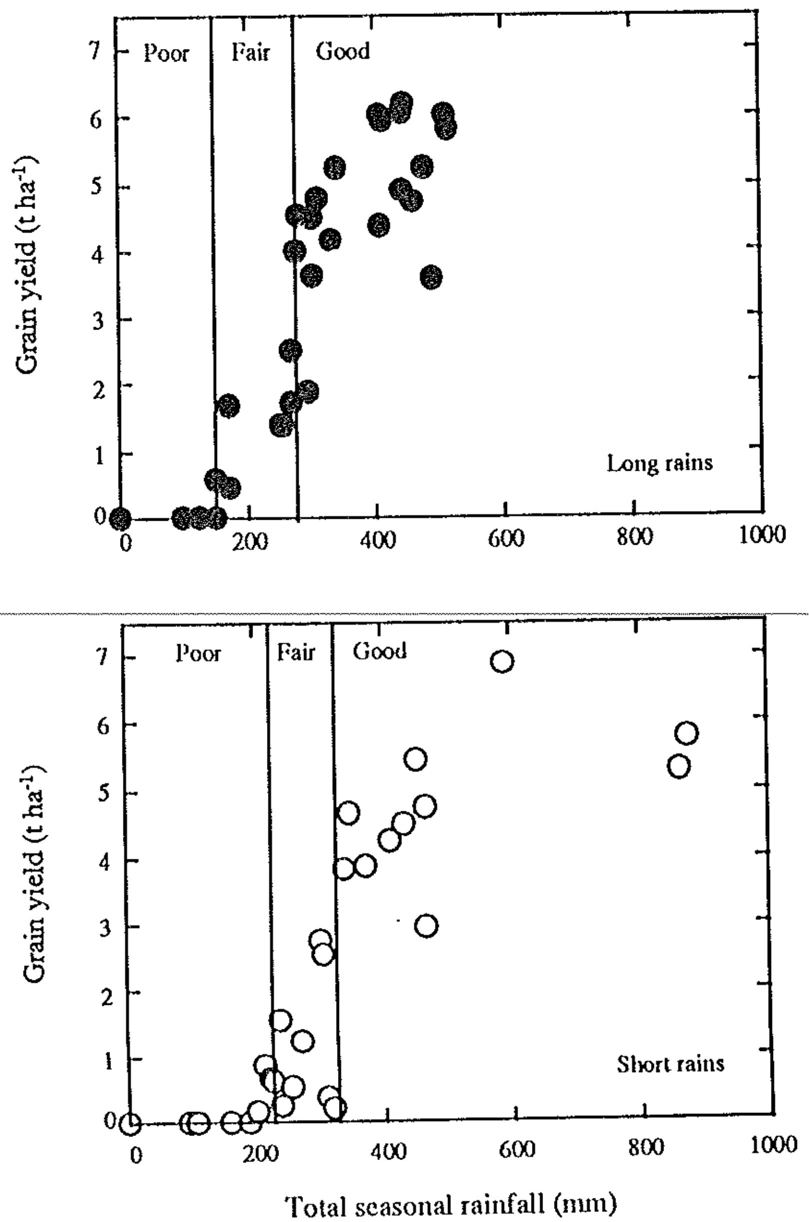

Fig. 3. The relationship between maize grain yield (S_5, Table 2a) and total rainfall during the maize growing season. Vertical lines distinguish season types according to Table 1c.

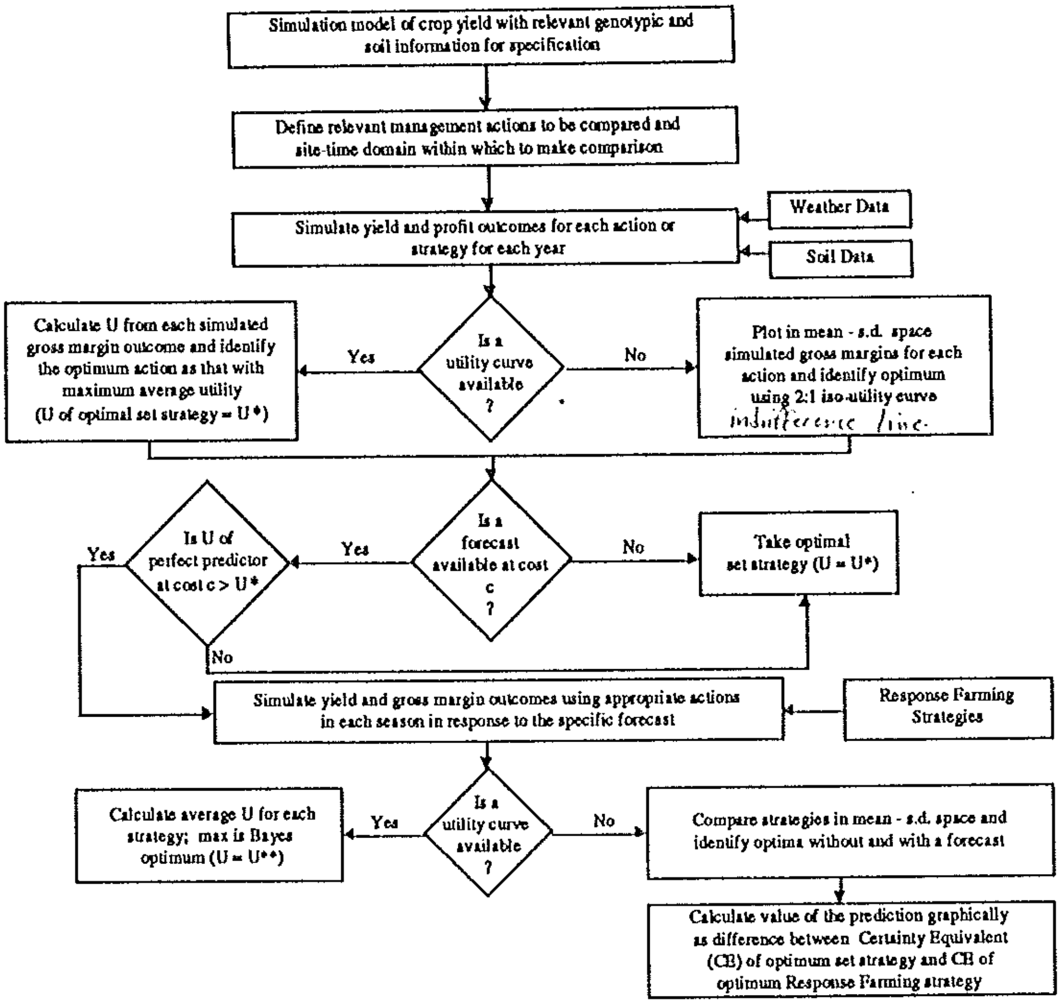

Fig. 4. Scheme for assessing the value of a rainfall predictor using a cropping system simulator. Adapted from Anderson *et al.* (1977).

performance mainly concerns comparisons of the probabilities shown in steps 3 and 5 in Fig. 2.

The second stage of evaluation concerns the impact of a predictor on economic performance (Fig. 4). The degree of success depends heavily on the ability of the model to simulate yield outcomes of relevant management actions over the range of seasonal conditions contained in historical rainfall records. The model used in this study is that described and validated by Keating *et al.* (1991) over a wide range of soil water, soil nitrogen, and maize plant densities. Simulations explained 88% of the variation in grain yield from 159 experimental observations (Fig. 3 in Keating *et al.* 1991). The 159 observations were mostly on-station experiments, including some in which water supply was varied using supplementary irrigation. However, several on-farm experiments which were researcher-initiated/farmer-managed studies, mainly with varying N fertiliser rates and population densities are included. Experiments were also conducted to test simulation of the effects of delays in thinning and fertilisation on crop performance (Wafula 1989). The soil properties and initial water and mineral N values at the beginning of each season of each year were the same as those used by Keating *et al.* 1991, except that nitrate concentrations in the top four layers were 1 ppm lower and organic carbon values were one third lower.

The performance of alternative agronomic strategies were compared using gross margins per hectare. These are calculated by deducting the variable input costs from gross returns from maize grain produced. Variable costs in the analysis (expressed in Kenyan shillings, Ksh) include seed (4 Ksh kg^{-1}), fertiliser N applied (30 Ksh kg^{-1}), and labour for thinning, harvesting, and shelling (3 Ksh h^{-1}). The price assumed for N is twice the purchase price to allow for variable costs of transport, additional weeding due to stimulation of weed growth, and as a hedge against an omitted cost. One variable cost omitted is that of amending phosphorus deficiency, a less common problem than N deficiency. Our main concern here is to avoid underestimating cost of fertilisation. The assumed sale price of maize grain is 3 Ksh kg^{-1}. Unit cost and price data were kept constant during the period simulated.

PERFORMANCE OF TWO PREDICTORS IN REDUCING UNCERTAINTY

The analytic framework used is that of Bayesian decision theory (Anderson *et al.* 1977). The problem addressed by Response Farming contains all the components of a decision problem (Anderson *et al.* 1977). Any yield-influencing *action* or *strategy* chosen by a farmer has an uncertain *outcome* in a given year due to uncertainty about the quantity of rain which will actually fall in that year. However, the frequency distribution of past types of season provides an indication of the long-term prospects for production and the probability of various outcomes for the pending season. This historical record is termed the *prior probability* distribution.

Table 3 shows the Bayes formula calculations for Predictor I, i.e. date of onset only. We are concerned with predicting the occurrence of any of three *states of nature* (θ_i), i.e. good, fair, or poor season types, as defined in Table 1c, using rules drawn from Tables 1a, 1b. The probabilities of each state occurring, based on rainfall records for Katumani for the past 32 years, are shown as prior probabilities ($P(\theta_i)$). In both long and short rainy seasons, the probability of either a good or a fair season is each approximately 0.4, and that of a poor season about 0.2 (Table 3).

When there is a source of additional information (e.g. P_I or P_{II}) which may more precisely indicate the type of season pending (a forecast), the performance of a predictor in forecasting the various season types is expressed as *likelihoods* or *conditional probabilities* (Tables 3 and 4; $(z_k|\theta_i)$). The likelihoods were calculated from historical daily rainfall data. The $P(z_1|\theta_i)$ (i.e. the probability of forecast 1 [early onset] given a good season) is calculated as the proportion of years in which early onset (as defined in Table 1) occurred in good seasons (i.e. the subset of years in which total seasonal rainfall was greater than 280 mm) (Table 1c). The probability of 1.00 for the long rains means that in every

Table 3. Bayesian probabilities for forecasts using date of onset (Predictor I) at Katumani Research Station from 1957 to 1988.

State θ_i	Long rains, Early onset (z_1): Prior $P(\theta_i)$	Likelihood $P(z_1\|\theta_i)$	Joint $P(z_1,\theta_i)$	Posterior $P(\theta_i\|z_1)$	Short rains, Early onset (z_1): Prior $P(\theta_i)$	Likelihood $P(z_1\|\theta_i)$	Joint $P(z_1,\theta_i)$	Posterior $P(\theta_i\|z_1)$
Good	0.37	1.00	0.37	0.65	0.40	0.72	0.29	0.53
Fair	0.41	0.42	0.17	0.29	0.44	0.50	0.22	0.40
Poor	0.21	0.17	0.03	0.05	0.15	0.25	0.04	0.07
	1.00	$P(z_1)$	= 0.57	1.00	1.00	$P(z_1)$	= 0.55	1.00

θ_i	Long rains, Late onset (z_2): $P(\theta_i)$	$P(z_2\|\theta_i)$	$P(z_2,\theta_i)$	$P(\theta_i\|z_2)$	Short rains, Late onset (z_2): $P(\theta_i)$	$P(z_2\|\theta_i)$	$P(z_2,\theta_i)$	$P(\theta_i\|z_2)$
Good	0.37	0.00	0.00	0.00	0.40	0.27	0.11	0.25
Fair	0.41	0.58	0.24	0.58	0.44	0.50	0.22	0.50
Poor	0.21	0.83	0.17	0.42	0.15	0.75	0.11	0.25
	1.00	$P(z_2)$	= 0.41	1.00	1.00	$P(z_2)$	= 0.44	1.00

season classified as good, onset occurred early. To quickly dispell the impression of early onset being a perfect predictor, note that early onset occurred in 42% of the fair seasons and 17% of the poor seasons as well.

The second stage in Predictor II is a forecast made possible by an *experiment*, which is the monitoring of cumulative rainfall for the 30 or 35 days following onset. In evaluating each weather predictor, the likelihoods of each forecast possibility ($P(z_k|\theta_i)$) are multiplied by the prior probabilities ($P(\theta_i)$) to calculate their *joint probabilities* ($P(z_k, \theta_i)$). Division by the total probabilities ($P(z_k)$) for the given forecast provides the *posterior probabilities* ($P(\theta_i|z_k)$). It is the probability of each type of season, given a specific forecast. This is the best estimate for the coming season, given the historical information and the forecast, and provides the logical probabilities on which to base tactical decisions. The revision of probabilities of events in the light of new information is the exceptional contribution of Bayesian decision theory.

The value of distinguishing between early and late onset in forecasting season type can be seen by comparing the prior probabilities with the posterior probabilities in Table 3. Without considering onset date, the probability of a "long rains" good season is 0.37. Recognition of an early onset "forecast" increases the probability of a good season to 0.65, and reduces the probability of a fair season from 0.41 to 0.29. There are low probabilities (0.05 for long rains and 0.07 for short rains) for an early onset being followed by a poor season. A late onset is a less accurate predictor of a poor season, although there is a low probability of a good season with a late onset.

Table 4 shows the Bayesian probabilities for Predictor II. The joint probabilities as well as the prior probabilities are the same as in Table 3. Comparisons of the posterior probabilities with those of Predictor I show that, in general, Predictor II substantially reduces uncertainty in seasonal rainfall compared to Predictor I (onset alone). Although there is a 0.26 (long rains) and 0.29 (short rains) probability that a forecast of a good season is followed by a fair season, the probability of a poor season following a good forecast is zero (based on this 32 year period). A poor season was predicted little better by Predictor II than by Predictor I.

The forecasting rules used here are those devised by Stewart (1988), and it is clear that their use materially reduces uncertainty. However, this is of economic value only if it results in different decisions with superior, more risk-efficient, outcomes, and this is the subject of the following section.

Table 4. Bayes formula calculations using forecasts from the rainfall experiment (Predictor II). (Joint probabilities are given in Table 3).

		Long rains			Short rains		
		Probabilities			Probabilities		
Forecast prediction	**State θ_i**	**Prior $P(\theta_i)$**	**Likelihood $P(w_k\|\theta_i)$**	**Posterior $P(\theta_i\|w_k)$**	**Prior $P(\theta_i)$**	**Likelihood $P(w_k\|\theta_i)$**	**Posterior $P(\theta_i\|w_k)$**
Good (k=1)	Good (i=1)	0.37	0.72	0.74	0.40	0.91	0.71
	Fair (i=2)	0.41	0.23	0.26	0.44	0.33	0.29
	Poor (i=3)	0.21	0.00	0.00	0.15	0.00	0.00
Fair (k=2)	Good (i=1)	0.37	0.90	0.14	0.40	0.00	0.00
	Fair (i=2)	0.41	0.46	0.86	0.44	0.25	0.58
	Poor (i=3)	0.21	0.00	0.00	0.15	0.50	0.42
Poor (k=3)	Good (i=1)	0.37	0.18	0.15	0.40	0.09	0.13
	Fair (i=2)	0.41	0.31	0.32	0.44	0.41	0.60
	Poor (i=3)	0.21	1.00	0.52	0.15	0.50	0.27

EFFECTS OF A WEATHER PREDICTOR ON ECONOMIC RETURNS AND RISK

This section compares several strategies for allocating yield-improving variable inputs. These strategies are shown as a "decision tree" in Fig. 5. A decision tree has decision nodes (shown as squares) and event nodes (circles). Primary interest is in the Response Farming strategy using P_{II}, but as in the previous section, inclusion of P_I allows the analysis to distinguish the forecasting contribution of w_k (using the amount of rain in the 30 or 35 days from onset, as in Table 2) from that of z_k (early or late onset). The simulation model makes the conditional decisions relating to these according to the information in Tables 1 and 2. The six Response Farming Strategies (R_1 - R_6) were combinations of P_I and P_{II} with different levels of maximum inputs, as in Table 2.

The reference point for the value of a within-season predictor is the performance of the optimal strategy that does not use such a predictor, i.e. that for which the prior probabilities of season type (Tables 3 and 4) provide the only predictor to guide variable fertiliser application and associated plant population density. Since the prior probability is essentially the same from year to year, allocation strategies can be predetermined. To find the optimal predetermined (Set) strategy (S_j), six serial fertiliser/plant population combinations were compared (Fig. 5).

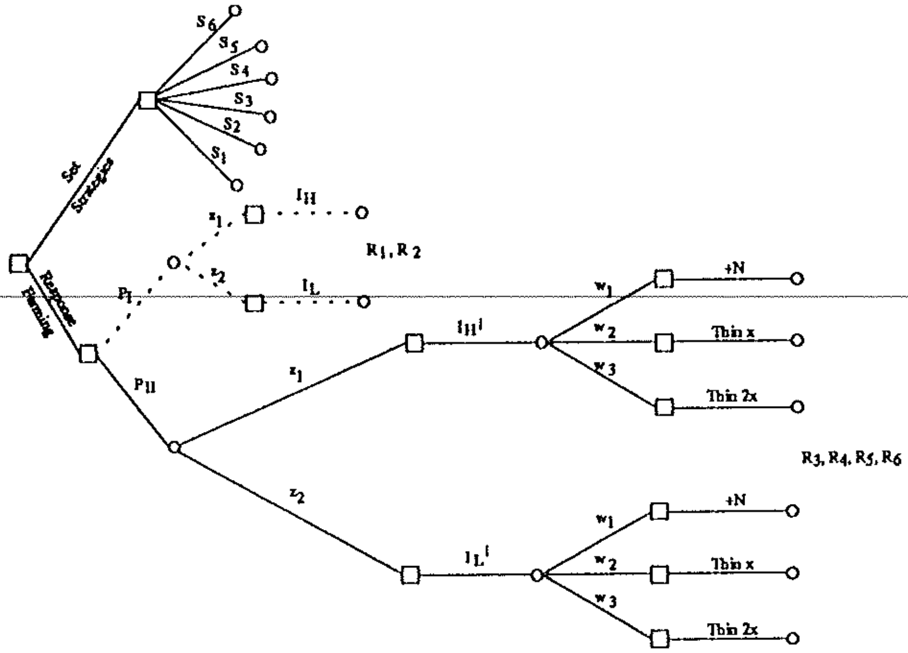

Fig. 5. A decision tree for alternative maize production strategies. Set strategies (S) and Response Farming strategies (R) are defined in Table 2. □ indicate decisions; o indicate the influence of weather/climate. Predictors (P) and forecasts (z,w) are defined in Table 1. Input responses (I_H, I_L), provisional input responses ($I_H{}'$, $I_L{}'$) and tactical responses to forecast w_k are defined in Table 2. The dotted branch (P_I) is included as a test of season onset alone as a predictor.

It can be seen from Table 2 that there is no low-input Response Farming level comparable to the lowest Set strategy. This is because Response Farming is a decision system for minimising the marginal risk associated with using fertiliser and associated variable inputs to increase yields. Improved capability to match inputs with the quality of the season can have little benefit, if input levels are invariably low.

The average yields and gross margins of alternative set strategies are shown in Fig. 6. Although average yields increased with even the highest inputs, gross margins were highest for strategies S_4 and S_5 in the long rains and with S_4 in the short rains. This, however, takes no account of the risk performance of these set input strategies.

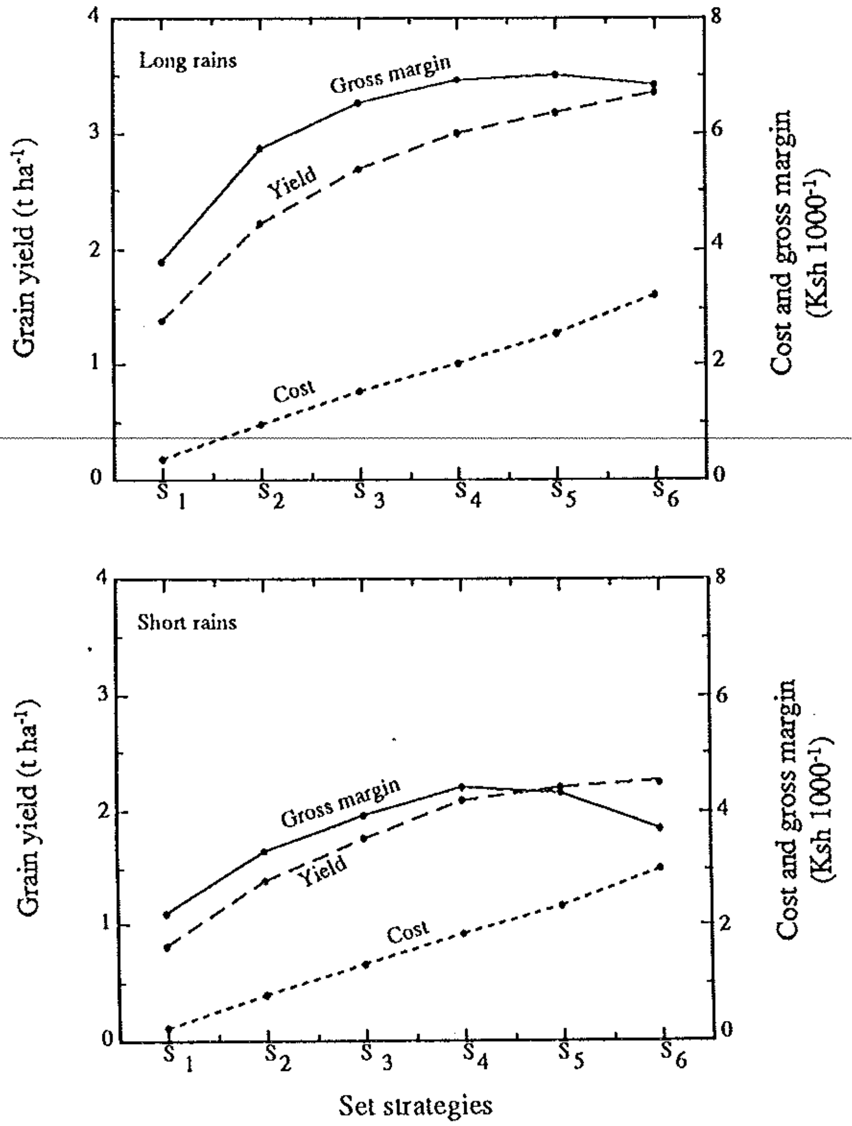

Fig. 6. Average yields, costs, and gross margins in long and short rainy seasons for six levels of inputs applied in every year (Set strategies).

A more informative picture of the effect of selected set strategies on yields and gross margins can be seen in Figs 7 and 8. The cumulative distribution functions of yield (Fig. 7) show the increased yield variability with higher inputs when yields do not increase in response to inputs in poor seasons. In fact, there is an indication of inputs reducing yield in poor seasons, especially in the short rains (i.e. the cumulative probability curves cross over). Poor seasons occur at Katumani with a probability of about 0.25 in the long rains and greater than 0.40 in the short rains. Substantial financial losses occur in these seasons if strategies with high variable inputs are used (Fig. 8). However, in the complementary class of better seasons, responses to the first increment of inputs (S_3) are quite spectacular.

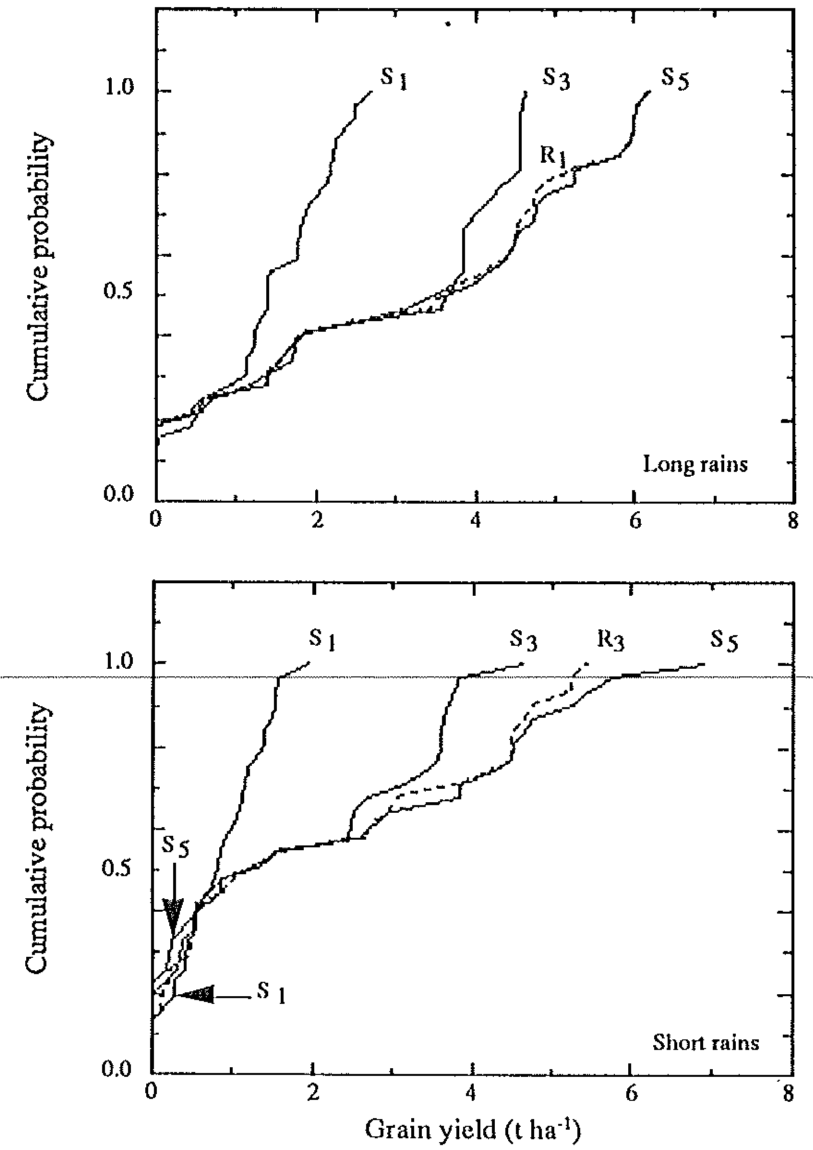

Fig. 7. Cumulative distribution functions for grain yield for S_1, S_3, S_5, and for the optimal Response Farming strategy in the long and short rains (strategies are defined in Table 2).

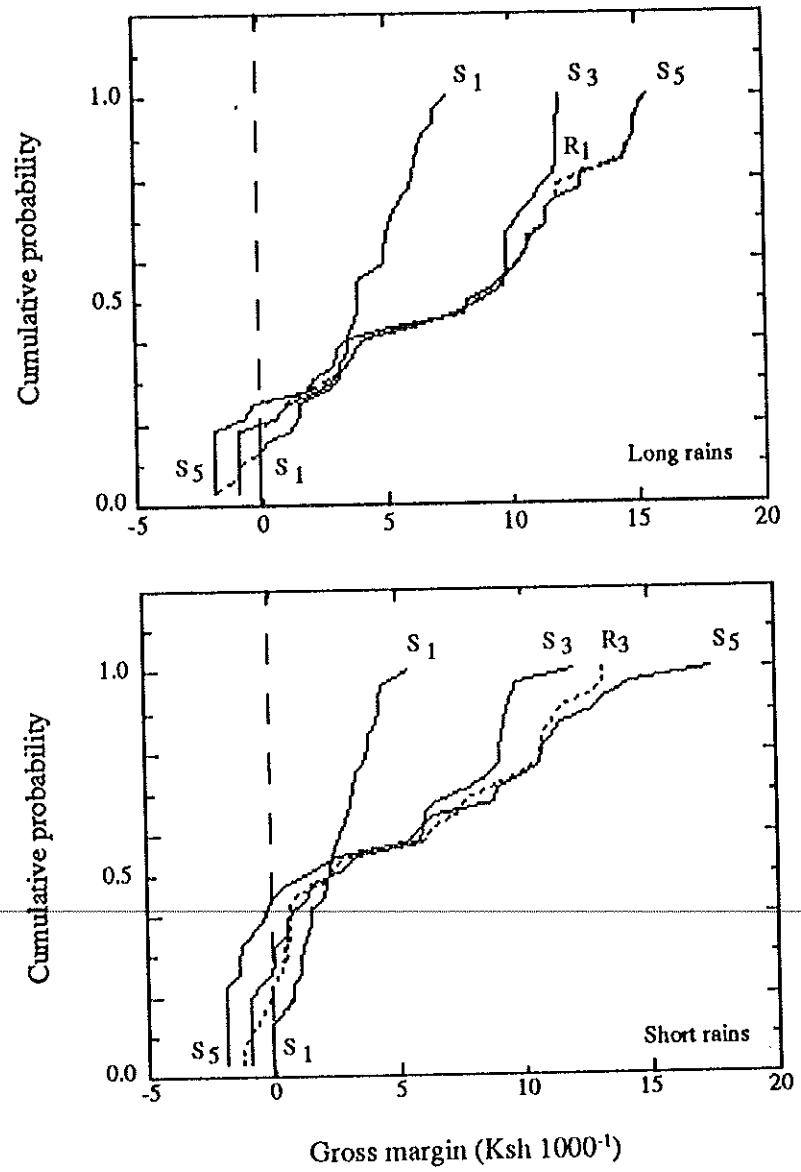

Fig. 8. Cumulative distribution functions for gross margin for S_1, S_3, S_5, and for the optimal Response Farming strategy in the long and short rains (strategies are defined in Table 2).

All farmers choose to take risks in order to gain greater returns, but they differ quantitatively in their attitudes toward risk (i.e. in their position on a spectrum from strongly risk averse, through risk neutral, to risk preferring). Case studies of the behaviour of farmers in Eastern Kenya indicate that virtually all farmers studied are at least moderately risk averse (Ockwell *et al.* 1991).

Recent research by L. Mohammed (unpubl. data) has quantified attitudes of a number of these farmers towards risk associated with using fertiliser and improved seed. Fig. 9 shows the utility curve for a "typical" farmer. This curve is an average of curves elicited from five farmers near Katumani using the

Equally Likely Certainty Equivalents method (Anderson *et al.* 1977). The method uses a game in which the interviewee is presented with a series of 50/50 lotteries covering a range of average monetary outcomes, in this case as actual quantities of fertiliser and seed. The procedure identifies the Certainty Equivalent (CE) for each lottery as the smallest value of a "gift" which he would prefer to a gamble for the larger amount, with a 50% chance of losing. The straight line in Fig. 9 represents the monetary values of the hypothetical 50/50 lotteries, i.e. the utility curve of a risk-neutral decision maker. For a given level of utility, the horizontal difference in monetary value between the two curves (d) is the "risk premium", i.e. the difference between the gift and the average, or expected, value of the gamble. This can be viewed as the cost of reducing risk to a tolerable level, or the increase in certain monetary return required to make a risk-averse farmer accept a risky prospect. In our analysis, the curve of Fig. 9 is used to transform gross margins to utility.

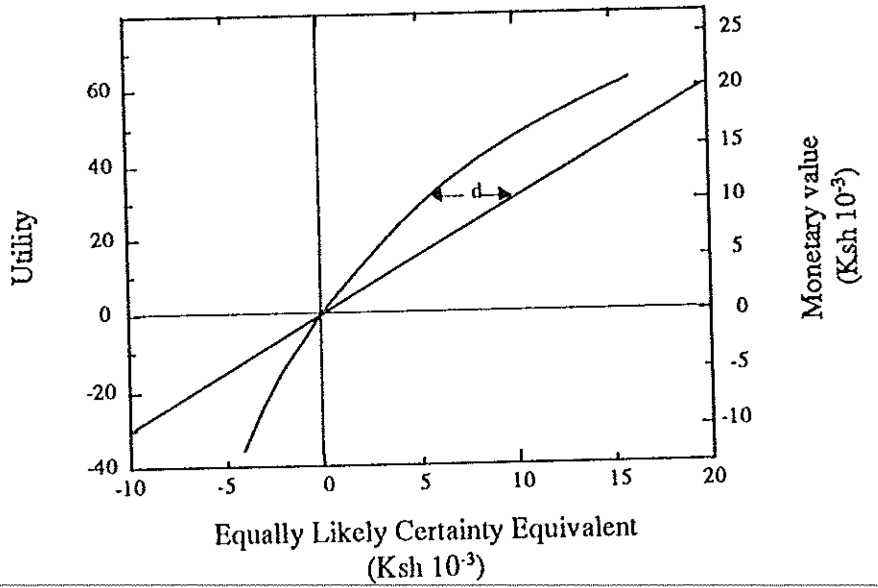

Fig. 9. A utility curve based on the average of five such curves of information elicited from selected farmers in Eastern Kenya using the Equally Likely Certainty Equivalent (CE) method. The straight line is the risk-neutral utility curve, and "d" is the risk premium.

Expected, or average, utility provides an index for ranking actions or strategies that combines the performance criteria of financial returns and risks. In the usual situation where performance data are scarce, expected utility must be calculated using elicited subjective probabilities for various classes of outcomes to derive a probability-weighted overall mean outcome. Here, since performance outcomes for all strategies in all years are simulated, average utilities for six set strategies can be calculated directly (Table 5). In both long and short rainy seasons, the strategy with maximum average utility, and thus the optimal strategy, is S_4, although it is only marginally superior to S_3.

Table 5. Average costs and utilities of Set strategies and Response Farming strategies. Optima are indicated by asterisks. (Strategies are fully described in Table 2.)

Strategy		Long rains Costs (Ksh 10^{-3})	Long rains Utility	Short rains Costs (Ksh 10^{-3})	Short rains Utility
Set					
S_1	22K, 0N	0.3	20.9	0.2	13.0
S_2	27K, 15N	1.0	28.5	0.8	17.9
S_3	33K, 30N	1.5	30.6	1.3	19.4
S_4	38K, 45N	2.0	31.0 *	1.9	19.9 *
S_5	44K, 60N	2.5	30.0	2.4	17.9
S_6	55K, 80N	3.2	27.6	3.0	13.3
Response Farming					
R_1	High, P_I	2.0	32.9 **	1.7	21.1
R_2	Medium, P_I	1.0	28.2	0.8	17.6
R_3	High, P_{II}	1.8	31.7	1.7	22.2 **
R_4	Medium, P_{II}	1.0	29.5	0.9	20.0
Perfect Predictor		39.0			30.2

Another means of comparing uncertain prospects of alternative choices of input levels is the so-called Mean-Variance analysis (Fig. 10). This is a valid framework when yield distributions are normal (Halter and Dean 1971). The relatively symmetrical curves in Fig. 7 indicate that this requirement is met. In this case, mean gross margins (m) are plotted against the corresponding standard deviation of gross margins (σ). Curves a-b (long rains) and c-d (short rains) represent sets of risk-efficient strategies comprising those strategies which dominate others by virtue of their higher m or lower σ. Any optimal strategy for the respective seasons must lie on this "efficiency frontier". The horizontal line e-f represents the choice criterion of a hypothetical farmer who is indifferent to risk. Drawn tangent to the efficiency frontier, a-b, the optimal Set strategy for this risk-neutral farmer is the one with the highest average profits, i.e. S_5. (S_5 entailed 44,000 plants ha^{-1} and 60 Kg ha^{-1} nitrogen (Table 2a)). A line similarly drawn for the short rains would identify the risk-neutral optimum between S_4 and S_5. This method identified the same optima as those generating the highest average gross margins in Fig. 6.

To many, using the concept of expected utility seems an abstract way of approaching the problem of assessing risky farm management choices. Additionally, it is not generally feasible to transform a utility curve into mean-variance or mean-standard deviation (m-σ) space as employed in Fig. 10 (J. R. Anderson pers. comm.). Binswanger and Sillers (1983) noted that the results of a number of published studies conducted in developing countries using experimental games of chance to elicit farmers' revealed preferences for taking risks, suggested the vast majority of them had moderate degrees of aversion to risk. The studies cited were conducted in India (Binswanger 1980),

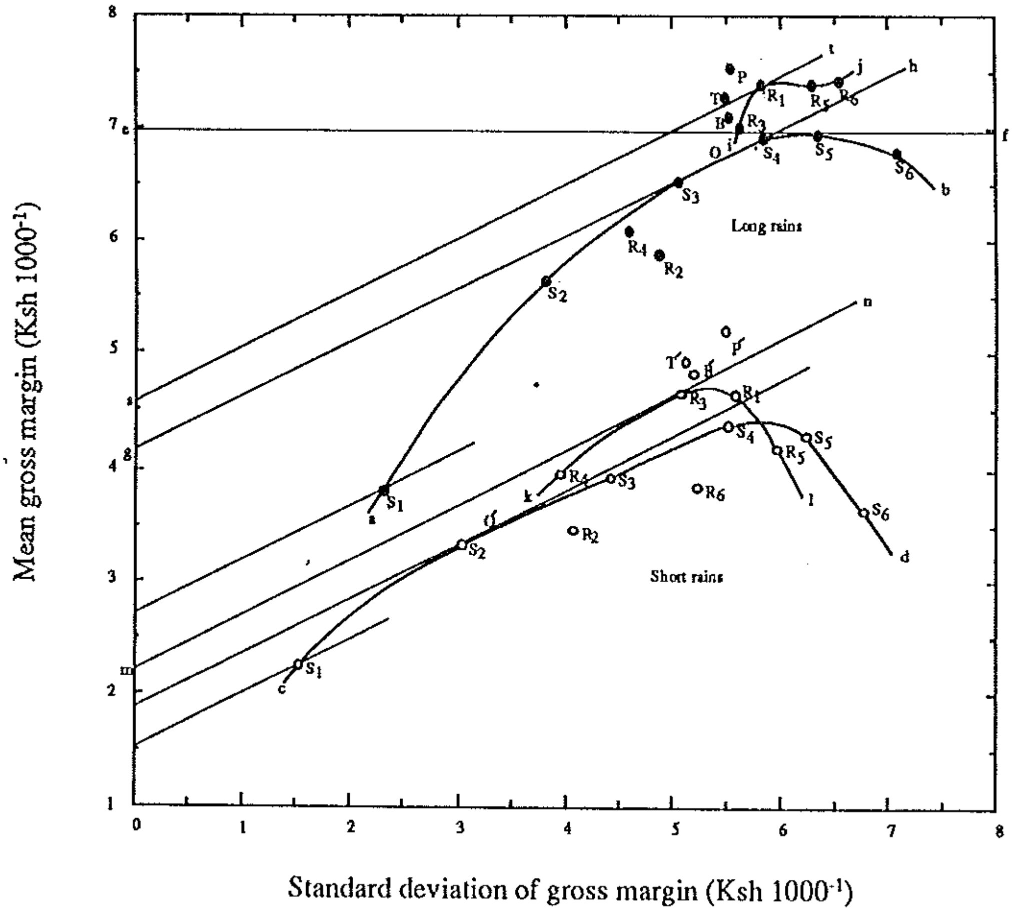

Fig. 10. The values of various strategies depicted in Mean-Standard Deviation (m-σ) space. Strategies differ in levels of inputs and use of a weather predictor as per Table 2. Curves are identified in text.

El Salvador (Walker 1980), Thailand (Grisley 1980) and the Philippines (Sillers 1980). Binswanger and Sillers (1983) demonstrate that there is a surprising degree of cross-cultural homogeneity in revealed farmer risk preferences in these studies when the stakes ranged from the current daily wage, up to about three months' wages.

Ryan (1984) suggests that these studies imply a rule-of-thumb of 2:1 as the slope of an iso-utility, or indifference, line reflecting the revealed attitudes of small farmers to incurring added risk versus extra profits or gross margins. The typical farmer would move left to right along efficiency frontiers, such as c-d and a-b in Fig. 10 as long as the increased standard deviation of gross margins is no more than twice as large as the increase in the mean gross margin. Hence, the 2:1 ratio of $\Delta\sigma/\Delta m$ represents the (inverse) slope of the tangent of the point where an indifference curve just touches the efficiency frontier. Barah *et al.*

(1981) used this 2:1 rule to rank sorghum cultivars for their yield and stability/adaptability from multi-location and multi-year trials in India.

We employ a similar rule in Fig. 10, where the line g-h has a co-tangent of 2:1. The typical farmers' level of utility or satisfaction would be maximised by operating on that part of the efficiency frontier where a 2:1 indifference line is just at a tangent to it. The higher the indifference line attainable, the greater the level of farmer utility, and the point of tangency is the highest attainable.

Using this 2:1 indifference line, the optimal Set strategy is indicated at "O" and "O'" for long and short rains. In the long rains, a farmer with the level of risk aversion expressed in the 2:1 line would prefer S_3 (average profits of about 6,500 Ksh ha^{-1} achievable with a little more than 33K plants and 30 kg N ha^{-1}) to S_5 (7,000 Ksh ha^{-1} which requires 44K plants and 60 kg N ha^{-1}). The optimal strategy in the short rains is just above S_2 (27K plants and 15 kg N ha^{-1} returning 3,300 Ksh) but, because a major segment of the efficiency frontier is nearly parallel to the indifference curve, S_2 has little advantage over S_3. Because the long rains efficiency frontier, a-b, has more curvature than that for the short-rains (c-d), the optimal strategy is less variant to changes in risk attitudes for the former than the latter. For example, in the short-rains (c-d) a 50% increase in the $\Delta\sigma/\Delta m$ ratio to 3:1 representing less risk aversion would imply an optimal strategy of near S_4 rather than S_2. In the long rains, a similar decrease in risk aversion would, at most, move the optimum towards S_4 from just beyond S_3.

Use of the Hypothetical Perfect Predictor

Thus far, we have identified the optimal Set strategy when a forecast is not available, following the flow diagram set out in Fig. 4. We resume this progress towards our goal of assessing the value of a Response Farming predictor at the arrow indicating an affirmative answer to the question in the centre of Fig. 4, "Is a forecast available at cost, c?" The next question in this flow diagram concerns the value of a predictor if it always provides correct forecasts. Although no predictor can be expected to do this, if the calculated utility of the hypothetical perfect predictor (adjusted for any costs) is not greater than the utility of the prior optimal Set strategy, then clearly there is no reason to continue the analysis and the optimal Set strategy should be adopted.

The gross margin outcomes simulated for Response Farming with a perfect predictor were again transformed using the utility function (Fig. 9), and average utilities calculated for each strategy over all years for both long and short rains. It can be seen from Table 5 that average utility with a perfect predictor (39 units) is considerably greater than the optimal Set strategy (31 units). The outcomes with perfect predictors in long and short rainy seasons are shown in Fig. 10 as "P" and "P'". Comparison of optimal set strategies (O and O') with Response Farming with perfect forecasts shows that perfect forecasts would substantially increase average gross margins, but with some increase in variability. A 2:1 iso-utility line through P (s-t) lies above that of one tangent to the optimal Set strategy (g-h), indicating that there is a potential utility increase from using a predictor, and there is reason to continue the analysis of the value of those which are less than perfect.

Choosing Optimal Response Farming Strategies

The average utilities for all Response Farming strategies for both rainy seasons are shown in Table 5. In both rainy seasons, high-input Response Farming strategies do result in higher average utility than the best Set strategy.

Curves i-j and k-l in Fig. 10 depict the efficiency frontiers for the Response Farming strategies with varying inputs and predictors in the long and short rains, respectively. Indifference lines with a 2:1 slope have again been drawn tangent to these frontiers, thus identifying the optima as strategy R_1 for the long rains and near strategy R_3 in the short rains. In decision analysis, the optimal strategy that utilises further information (vis à vis the Set strategy) is termed the Bayes strategy, and can be expected to have an average utility which lies between that of the prior optimum (Set strategy) and the Bayesian outcome using the perfect predictor (Winkler *et al.* 1983). By comparing the positions of the indifference lines, it is clear that the optimal Response Farming (Bayesian) strategy for both the long and short rains is closer to that of the perfect predictor than it is to the optimal Set strategy. This attests to the value of Stewart's (1988) prediction rules.

The Economic Value of Response Farming

Just how valuable could Response Farming be to a farmer in this district of Kenya? While average utility provides a single index for ranking the performance of alternative strategies, because it is dimensionless and of arbitrary scale, it cannot quantify the value of a predictor. However, differences between strategies can be quantified by comparing differences in gross margins between indifference lines at a common level of risk (value of σ in Fig. 10). When this is done at the y axis (σ = zero), comparisons are among the CEs of strategies. Using this method, it can be seen that the average value of the best Response Farming strategy in the long rains is about 450 Ksh, (i.e. s-g in Fig. 10) or only about 11% higher than the optimal Set strategy. In the short rains, the average improvement is about 330 Ksh, or about 18% higher than the optimal Set strategy where mean gross margin is only 1,800 Ksh.

How good the predictors are can also be judged in relation to the outcome using the hypothetical perfect predictor. In the long rains, if the prediction of season type was perfect, the average benefit would be another 300 Ksh, which is a surprisingly small increment (vertical distance from point P to line s-t). In the short rains, a perfect predictor would add a further 500 Ksh profit per season (vertical distances from point P' and line m-n).

Relative to the strategy in which no fertiliser is used (S_1 in Fig. 10), and corresponding closely to the practice of most farmers in the region, the benefits of Response Farming can be partitioned into: (a) the effects of inputs of fertiliser and corresponding higher plant populations; and (b) the effects of more efficient application of inputs due to information (forecasts) about the seasonal rainfall. In the long rains, the effect of adopting the optimal Set strategy (near S_3) is to increase the CE by 1,400 Ksh (from 2,650 at S_1), i.e. by 53%. The optimal Response Farming strategy increased the CE by another 450 Ksh, an additional 11%. In the short rains, the optimal Set strategy (near S_2)

increased the CE by 300 Ksh (from S_1 = 1,500), i.e. by only 17%. The optimal Response Farming strategy provided a further increase of 330 Ksh, or 18%. Hence it is use of inputs, especially in the long rains, that provides the greatest benefits. The value of the forecast, while not trivial, is modest by comparison.

Comparison of Predictors I and Predictor II

We expected the two-stage predictor, P_{II}, to be superior to P_I (onset date only), and although this was the case in the short rains (CE of $R_3 > R_1$), the opposite occurred in the long rains. Part of the explanation of the latter is that onset alone is more efficient in predicting a good season in the long rains than in the short rains (Table 3), and was nearly as good as P_{II} (Table 4). Moreover, there is a cost of a second stage predictor that, while included in the analysis, is not apparent. This is the cost of keeping options open for 30 or 35 days. The points "T" and "T'" in Fig. 10 are the outcome of a hypothetical scenario, in which the crop production settings achieved by the second stage agronomic adjustments (in response to the second stage of P_{II} information) are imposed with perfect foresight at the time of planting. The gain in efficiency has two causes. The first is a cost saving. For example, avoiding the cost of planting a high population for the contingency that a good season follows (but doesn't), plus the additional cost of thinning to the appropriate population for the fair or poor season forecast at stage 2. The second is improved biological efficiency of when appropriate plant populations and N levels are synchronised. Of these two, the first was the more important; points "B" and "B'" in Fig. 10 represent cases that differ from "T" and "T'" only because costs of R_3 were applied, i.e. differences reflect solely the effects on the biology of the crop.

Why Are Most Farmers' Strategies So Far From the Optimum?

If the yield simulator is performing realistically and our analysis of the output is correct, and if the strategy of most farmers in the district is approximately represented by S_1, why do these farmers forego so much income and satisfaction by their failure to use fertiliser together with higher plant populations, with or without Response Farming? Four possible explanations are:

(i) The estimated responses in mean gross margins to increases in fertiliser and plant population are too high;

(ii) Farmers in the district are much more risk averse than the 2:1 line indicates and a line of steeper slope properly representing their risk attitudes would identify S_1 as the optimal strategy;

(iii) Farmers perceive the m-σ efficiency frontiers which they face in maize production to be much flatter than the frontier simulated in Fig. 10, i.e. the slope may be low enough to identify S_1 as optimal, using the 2:1 iso-utility curve; and

(iv) Farmers have access to insufficient capital to adopt more optimal strategies.

The first explanation must be accepted to some degree, since the model at present does not include the effects of weeds, insects, or diseases. Neither is the cost of weeding increased with fertiliser rate.

For explanation (ii) to be valid, these farmers would be very much more risk averse than farmers in similar circumstances (Ryan 1984), and much more risk averse than indicated by the utility curve of the most risk-averse farmer in the sample of Kenyan farmers. The 2:1 indifference line depicted a somewhat higher degree of risk aversion than the average utility curve in Fig. 9 (judging by the differences in optimal strategies selected in Fig. 10 and Table 5). As mentioned earlier, because of the slight curvature of the efficiency frontier for set strategies in the short rains, the optimal point is quite sensitive to changes in the indifference line. Even so, the slope of the indifference line ($\Delta\sigma/\Delta m$) would have to be near 1:1 before S_1 would appear optimal in either season. This would classify these Kenyan farmers as severely risk averse, which in other studies constituted only 1-3% of those assessed. We would hence tend to reject this explanation for non-adoption.

Explanation (iv) must be of some importance. The cost of fertilising in the optimal Response Farming strategy is equivalent to 60-100 days of labour wages, and there are no institutions which provide credit for such purposes. On the other hand, there is no evidence that the majority of farmers use even a small amount of fertiliser on a small proportion of a field, an outlay which many could afford. Significantly, the few farmers that we have found using fertiliser on maize have no doubts about its beneficial effects on their incomes.

We lean towards explanation (iii) and await with interest the outcome of current research being carried out to study farmers' perceptions of their risks, and income opportunities as they begin to use fertiliser. Explanations (i) and (iii) are complementary. Once better information on farmers' perceptions of risks is available, sensitivity tests of discounting of simulated yields for pests and diseases, as well as the inclusion of variable costs of weeding, will be valuable. Simulated outcomes with realistic discounting, that still result in an efficiency frontier that has a much steeper slope than one revealed by new information about farmer perceptions, would indicate that education and demonstration of the value of using N fertiliser should be an urgent priority . This would be a striking contrast to the present situation in which local research emphasis is placed on constraints other than soil fertility (and of generally lower importance) due to the apparent interpretation by agricultural professionals that, because few farmers use fertiliser, this technology is not appropriate.

DISCUSSION OF RESPONSE FARMING AND THE KENYAN CASE

One of our aims in this paper was to critically assess the merits of Response Farming. We believe that the framework of decision analysis greatly aids this. Stewart's (1988, 1991) near-avoidance of the decision analysis framework in his writings may have been intended to protect the reader from unfamiliar concepts and terminology, but a consequence has been to make Response Farming appear deceivingly unique and appealing. We view the early work by Stewart and colleagues as visionary. Our analysis confirms that they developed remarkably effective forecast criteria for Eastern Kenya. The procedure used to develop Response Farming, summarised in Fig. 2, is a straight-forward procedure which uses agroclimatic analyses and Bayesian statistics that enables new intra-seasonal information to contribute to multi-stage crop production decisions. In addition to a clear understanding of Response Farming, potential users have until now lacked a way of knowing how much attention should be given to testing and implementing this scheme.

From our analysis, we would conclude that no special action is warranted at this time. However, both research and extension staff should understand the concepts, recognise them as basically sound, and consider them relevant to strategies for increasing production through higher inputs of fertilisers and higher plant populations under some circumstances. If, however, as is commonly believed, it is rare for farmers at the low end of the technology/yield spectrum to move to the economic optimum in one step, then Fig. 10 indicates that Response Farming is not likely to be an attainable first step for farmers currently using S_1 (no fertiliser). The more important first step for these farmers is to use moderate inputs of fertiliser, and progressively move toward the optimal Set strategy. This is superior to using Response Farming with low inputs (R_2, R_4). For farmers with a high input/high yield strategy firmly in place and wishing to extract greater benefits, a strategy which uses high inputs only in response to forecasts of good seasonal prospects can be expected to be attractive. Indeed, we have observed that the few farmers who use relatively high fertiliser rates split their applications, and apply later portions only when there is abundant rain in the first few weeks following planting. It may be that the principles of Response Farming are so generally intuitive that when conditions are conducive to adoption, no special extension of a formal Response Farming scheme will be necessary.

In a climate where rainfall is highly variable, yields will have much lower variability when crops are prevented from reaching water-limited yields by some factor (e.g. N) which is even more limiting. Relief of the N constraint results in more efficient use of the water resource, higher average yields and profits, and higher variability (Fig. 10). Clearly this increase in variability cannot be viewed as necessarily undesirable. Response Farming clearly does provide a strategy which is superior to an annual application of any set amount of fertiliser, but this strategy is the optimum in spite of greater variability. Decision analysis methods, such as the m-σ framework in Fig. 10 provide a basis for identifying acceptable trade-offs between profit and variability. Their value in linking crop systems simulation to the development of decision aids is readily apparent.

Although we have focused on a small region in Kenya in this paper, the value of a seasonal rainfall forecast is an issue of global importance. In many parts of the world, seasonal rainfall forecasts that are obviously useful to farmers are unlikely to be provided by meteorological services in the near to medium future. However, as our analysis for Kenya shows, a forecast can be wrong, disturbingly often, and yet the predictor can still be economically valuable. "How valuable?" can be estimated using a crop yield simulation model, historical rainfall data, and decision analysis procedures as described in Fig. 4. When the predictor requires weather data not normally recorded, it is more difficult to determine the likelihoods (conditional probabilities) needed for revision of prior probabilities of season types. However, in the case of the Southern Oscillation Index, historical barometric pressure information enables the forecasts to be made for each season in retrospect, and the predictor can be evaluated experimentally (Hammer and Muchow 1991; Clewett *et al.* 1991).

Although initiated as an analysis of Response Farming, this study highlights an issue of greater importance in Eastern Kenya. The evidence is overwhelming that, as Ruthenberg (1980) predicted for this type of farming system, soil fertility has become the major limiting production factor in this climatically risky region. This preliminary economic analysis indicates that use of fertiliser on appropriate population densities of maize, with or without Response Farming decision strategies, may be highly profitable despite the fact that few farmers and scientists appear to recognise this. Given the severity of the economic and ecological problems of this region, the intense interest of aid donors in solutions, and the paucity of other promising technical innovations, this analysis indicates that a re-assessment of the potential role of N and phosphorus fertilisers on small farms in Eastern Kenya is warranted. A logical first step would be a more comprehensive and extended analysis than this one with: (a) more attention to assessing the costs of adopting these yield-improving practices; and (b) analyses for additional locations.

CONCLUSIONS

Although most agricultural scientists are quite unfamiliar with decision analysis, most of the concepts and methods have been well established for over two decades. Byerlee and Anderson (1969) and Doll (1971) reported analyses of the value of weather predictors for crop production conducted with much the same objective and in much the same analytical framework as ours. What has changed is the availability of: (i) methods for estimating yield in relation to both controlled and climatic variables (e.g. dynamic models (Easterling and Mjelde 1987) and simulation models), thus providing more realistic mean-variance (or m-σ) efficiency frontiers; and (ii) more robust estimates of the risk attitudes of farmers, which can be used to identify the most risk-efficient strategies. Byerlee and Anderson (1969) resorted to assuming that South Australian wheat farmers were risk neutral in order to escape the problem of lack of data on variability over time as it related to varying input rates. Doll (1971) was limited by availability of experimental data to conducting an analysis using only seven years, with a different production function for each year. This data-scarcity problem contrasts with the readiness with which we were able to generate a yield value for each relevant action or strategy in both seasons in all years for which rainfall data exist. This capability was not developed without cost, but the existence of a robust maize growth model, with its performance validated elsewhere, greatly reduced the marginal cost of developing a model with adequate performance in Eastern Kenya. Admittedly, this cost is too high for most *ad hoc* economic analyses. However, as analyses which use a valid model become better appreciated as the key to efficient research for improved management, the research needed to tailor an existing model to a region is likely to be increasingly viewed as a priority.

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