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ADDING VALUE TO FIELD-BASED AGRONOMIC RESEARCH THROUGH CLIMATE RISK ASSESSMENT: A CASE STUDY OF MAIZE PRODUCTION IN KITALE, KENYA

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SUMMARY

In sub-Saharan Africa (SSA), rainfed agriculture is the dominant source of food production. Over the past 50 years much agronomic crop research has been undertaken, and the results of such work are used in formulating recommendations for farmers. However, since rainfall is highly variable across seasons the outcomes of such research will depend upon the rainfall characteristics of the seasons during which the work was undertaken. A major constraint that is faced by such research is the length of time for which studies could be continued, typically ranging between three and five years. This begs the question as to what extent the research was able to 'sample' the natural longer-term season-to-season rainfall variability. Without knowledge of the full implications of weather variability on the performance of innovations being recommended, farmers cannot be properly advised about the possible weather-induced risks that they may face over time. To overcome this constraint, crop growth simulation models such as the Agricultural Production Systems Simulator (APSIM) can be used as an integral part of field-based agronomic studies. When driven by long-term daily weather data (30+ years), such models can provide weather-induced risk estimates for a wide range of crop, soil and water management innovations for the major rainfed crops of SSA. Where access to long-term weather data is not possible, weather generators such as MarkSim can be used. This study demonstrates the value of such tools in climate risk analyses and assesses the value of the outputs in the context of a high potential maize production area in Kenya. MarkSim generated weather data is shown to provide a satisfactory approximation of recorded weather data at hand, and the output of 50 years of APSIM simulations demonstrate maize yield responses to plant population, weed control and nitrogen (N) fertilizer use that correspond well with results reported in the literature. Weather-induced risk is shown to have important effects on the rates of return ($ per $ invested) to N-fertilizer use which, across seasons and rates of N-application, ranged from 1.1 to 6.2. Similarly, rates of return to weed control and to planting at contrasting populations were also affected by seasonal variations in weather, but were always so high as to not constitute a risk for small-scale farmers. An analysis investigating the relative importance of temperature, radiation and water availability in contributing to weather-induced risk at different maize growth stages corresponded well with crop physiological studies reported in the literature.

INTRODUCTION

In sub-Saharan Africa (SSA) where rainfed agriculture is the dominant source of food production accounting for nearly 90% of staple food production (Rosegrant *et al.*, 2002), there has been a wealth of agronomic and crop improvement research that stretches back to 1950 and often before. Factors such as time of sowing, plant

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population, weed control measures, fertilizer use, improved rainfall management through mulching or contrasting tillage techniques and their interaction with contrasting crop species and improved crop genotypes have been extensively studied and reported. Typical of such research was that undertaken between 1965 and 1969 at the Grasslands Research Station, established in 1951 in Kitale, Kenya for, the new hybrid maize (*Zea mays*) varieties that were being developed and released at that time (Allan, 1972).

However one factor that constrained, and still constrains, such work is the length of time that such studies could be continued. Typically, in the past, few of them have exceeded four to five years and more recently evidence suggests that even shorter-term studies are becoming the norm. A recent compilation of field-based research on integrated soil fertility research in SSA (Bationo *et al.*, 2007) presented the results of 105 pieces of integrated soil fertility related research. Of these, 57 were field-based agronomic studies that covered a wide range of innovations including nitrogen (N) and phosphorous (P) fertilizers, the use of farmyard manure and the inclusion of leguminous crops and trees in rotations. Studies of interactions with contrasting water conservation approaches such as the use of mulches and contrasting soil tillage were also reported in several papers. Of these studies, thirty were for 1 year or less, eleven for 2 years, ten for 3 years, three for 4 years, one for 5 years and one for 7 years. Whilst most of these papers presented information on rainfall and rainfall ranges at the study sites, none related the results obtained to the prevailing weather conditions. The results of one long-term study (14 years) undertaken in Kenya (Kihanda *et al.*, 2007) was an exception in that an attempt was made to explain season-to-season variability in crop responses to both manure amounts and to total seasonal rainfall through regression analysis.

This begs the more general question as to what extent the rainfall seasons over which such investigations were undertaken are able to 'sample' the natural season-to-season and within season variability of rainfall, that is so evident in SSA, especially in the drier areas. This variability is illustrated in Figure 1 which presents the long-term (>30 years) mean seasonal rainfall totals from a range of locations in Eastern and Southern Africa and their coefficients of variation (CV). It can be seen that the inherent variability in seasonal rainfall totals increases disproportionately as one moves from wetter locations to the semi-arid tropical (SAT) regions that receive between 250 and 600 mm of seasonal rainfall (Cooper *et al.*, 2008). Whilst seasonal rainfall totals themselves exhibit high variability, rainfall totals over shorter periods, perhaps corresponding to moisture sensitive stages during crop growth such as germination and flowering exhibit even greater variability.

The magnitude of such seasonal rainfall variability can be further illustrated (Figure 2) by the probability distribution of the long-term seasonal rainfall data from Bulawayo, Zimbabwe (1952–2007) where seasonal rainfall totals have a mean value of 604 mm and a CV of 28%, with totals ranging from 179 to 1029 mm.

Since rainfall, stored in the soil profile, is the only source of water available for crop growth and yield development, such magnitudes of variability of water supply are likely to have profound impacts, not only on crop yield, but also on the potential

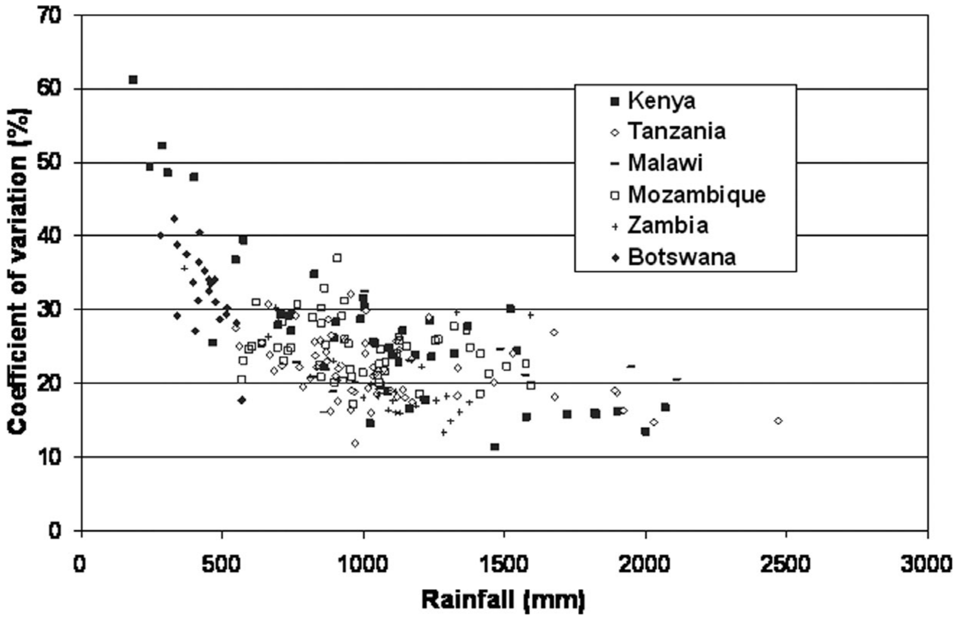

Figure 1. Means of seasonal rainfall totals (mm) and their coefficient of variation (%) for locations in Eastern and Southern Africa (Cooper *et al.*, 2008).

beneficial effects and rates of return that farmers may expect to receive from the adoption of innovative crop, soil and water management practices and indeed for the correct choice of crop variety or species. Not surprisingly, such effects have been noted by researchers in the past. For example, Jones (1987) found that the optimum plant population of sorghum (*Sorghum bicolor*) in the SAT of Botswana ranged from 25 000 to 69 000 plants ha^{-1} over a rainfall total range of 200–700 mm in the seasons of the study, and Smaling *et al.* (1992), based on 70 trials over four years in contrasting agro-ecological zones in Kenya, noted that, in three years out of the four, farmers could achieve rates of return of maize yield responses to fertilizer input that ranged from 1.5 to 4.5, again depending on rainfall amounts. In seasons of very low rainfall, rates of return fell below 1.

However as noted above, field-based investigations are hardly ever of sufficient length to establish robust relationships between rainfall amounts and its distribution and the resultant crop responses to contrasting management practices.

Given the (i) large variations of seasonal rainfall, (ii) the impact that rainfall amounts and distribution will have on the results obtained through agronomic research and (iii) the questionable ability of four to five seasons of research to capture the full extent of the longer-term rainfall variability, it is important that approaches to more detailed climate-induced risk analyses to accompany field-based research should be evaluated. Without such risk analyses, farmers cannot be properly informed about the full nature of such risk and the extent to which modifications to crop, soil and water management recommendations may be made to mitigate the extent

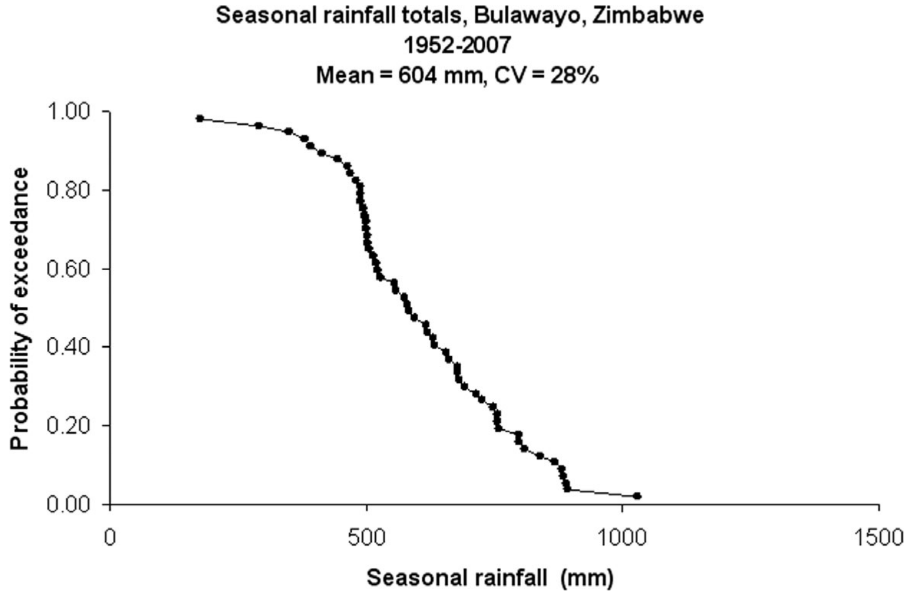

Figure 2. The probability of exceeding any given seasonal rainfall total (mm) at Bulawayo, Zimbabwe (1952–2007).

of such risk. Given the risk averse nature of small-scale farmers in SSA, this is important.

One way to address this is through the use of crop growth simulation models such as the Agricultural Production Systems Simulator (APSIM), which is a crop simulation model which simulates the dynamics of crop growth, soil water, N and soil carbon in a farming system (McCown *et al.*, 1996). It operates on daily time steps and when driven by long-term (>30 years) daily weather data, can be used to predict the impact of seasonally variable rainfall, both amounts and distribution, on the climate-induced risk associated with a range of crop, water and soil management strategies. APSIM can simulate the impacts of such contrasting management options on a range of crops amongst which maize, sorghum, pearl millet (*Pennisetum americanum*), chickpea (*Cicer arietinum)*, pigeon pea (*Cajanus cajan*), soyabean (*Glycine max*), groundnut (*Arachis hypogea)* and sunflower (*Helianthus annuus)* are likely to be of most interest in SSA. When properly calibrated for these crops, APSIM can provide an accurate simulation of actual crop yields across a range of soil types and seasons (e.g. Dimes, 2005).

APSIM has been used in the tropics of sub-Saharan Africa by various researchers to model fertilizer responses (Shamudzarira and Robertson, 2002), interactions between previous leguminous crop and maize responses to N (Robertson et al., 2005) and crop–weed interactions (Chikowo *et al.*, 2008; Grenz *et al.*, 2006).

However, often the existence, availability, access to, or required cost of high-quality, long-term daily weather data for locations of interest can present very serious constraints to the use of such models in SSA. Structural reform policies in the 1980s encouraged national meteorological services to treat long-term historical weather data as a source of revenue rather than a public good, and the reporting from an already inadequate number of stations is declining (Washington *et al.,* 2006, see also Hansen *et al.,* 2011).

In such instances, the use of spatial weather generators such as MarkSim can help overcome this constraint. MarkSim is a spatially explicit daily weather generator that was released in 2002 and is a weather generator which uses a third order Markov chain process to generate daily weather parameters. It is specifically developed to generate weather data for tropical regions. The climate surfaces that are produced use data from 10 000 stations in Latin America and 7000 from Africa. MarkSim relies on climatic data surfaces interpolated from weather stations and generates synthetic rainfall records that are statistically similar to long-term patterns on a grid basis of 18 km × 18 km (Jones and Thornton, 2000).

Given the need for information on climate-induced risk and the availability of well-tested crop growth simulation models and spatial weather generators, the objectives of this study are:

1. To demonstrate the value of such tools in climate risk assessment to compliment field-based research.

It is often felt that climate-induced risk is only likely to be of serious consequence in more arid environments where rainfall amounts are low and highly variable (Figure 1), so a secondary objective of this study was:

2. To assess the value of the outputs of such analyses in the context of a high potential maize production area (in this case, Kitale, Kenya) where intuitively climate-induced risk might be assumed to be unimportant.

The outputs of this work are related to the recommendations that were produced by Allan (1972) for new long-duration maize hybrids (180 days to maturity) in Kitale with special reference to recommendations concerning plant population (44 000 plant ha^{-1}), weed control (weeding at five weeks post emergence) and N fertilizer use (30 kg N ha^{-1} at sowing plus120 kg N ha^{-1} at five weeks post emergence). Whilst the research was undertaken by Allan more than 40 years ago, the recommendations that resulted from this work are still being widely followed today in the high potential maize production zones of Kenya. This climate-induced risk analysis thus remains relevant.

MATERIALS AND METHODS

Location

The study location, Kitale (1°1′N, 35°0′E, altitude 1890 m asl) is situated in the Trans Nzoia district of Western Kenya. The region is considered a high potential maize growing area and receives an average annual rainfall (1951–1986) of 1259 mm, distributed in a uni-modal rainfall pattern largely between March and October. Long-duration maize hybrids are widely grown. The average annual maximum and minimum temperatures are 25.4 °C and 11.5 °C, respectively (FURP, 1987). The

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topography is largely gently undulating and the dominant soils are deep well-drained sandy clay loams (rhodic Ferralsols).

Weather data generation using MarkSim

MarkSim has the option to either (a) generate weather data either using the location co-ordinates and elevation as input to estimate weather parameters from interpolated surfaces that have been incorporated in the MarkSim software or (b) by using long-term (20–25 years) averages based on daily weather data of the location of interest (Jones and Thornton, 2000). In this study the long-term maximum and minimum temperatures and rainfall averages (FURP, 1987) were used to generate 50 years of daily weather data (maximum and minimum temperature, rainfall and solar radiation) for Kitale. The generated weather data were ready to use as an input into APSIM.

Available weather data

Daily weather parameters have been recorded at Kitale continuously since 1936 for the township and since 1951 for the Grasslands Research Station. However, currently the cost of access to this daily data is prohibitive. Free access to such data is possible through the National Oceanic and Atmospheric Administration (NOAA), USA (ftp://ftp.ncdc.noaa.gov/pub/data/globalsod); however, records held there for Kitale only date back to 1975 and are of poor quality with many missing values. Of the 33 years held on the website, only 16 years were of sufficient quality (< four days missing for the April to September growing season) to be of use in assessing how well MarkSim simulated rainfall amounts and distribution patterns at Kitale.

Calibration of APSIM

The calibration was based on that already existing in APSIM for Hybrid 614 and modified for Hybrid 6302, a very similar hybrid with regard to maturity type and yield potential. Crop growth data were abstracted from Cooper (1979) together with the base temperature calculated in that paper of 9 °C. Thermal time requirements for the development stages (i) emergence to end of juvenile phase, (ii) end of juvenile phase to flag leaf initiation and (iii) flag leaf initiation to 50% tasselling were adjusted to obtain the best fit between observed and simulated crop growth and yield.

Other inputs required for APSIM include the soil water retention parameters, e.g. water content at saturation, field capacity and permanent wilting point along with the soil bulk density. Soil organic carbon values are also required. This information was available in detail to a depth of 210 cm (Cooper and Law, 1977). A total of 239 mm of water was available up to the depth of 205 cm. The maximum available water to the crop was set at 40% of the total available water, i.e. 96 mm. The initial mineral N of the soil profile was set at 15 kg ha^{-1} NO_3 and 10 kg ha^{-1} NH_4. For the purposes of this study, P was assumed to be non-limiting in all simulations although Allan (1972) reported frequent responses to P in the soils of the Trans Nzoia district and indeed recommended a dressing of 500 kg ha^{-1} of single super phosphate at sowing.

The sowing rule was set so that sowing took place when there was an accumulation of 50 mm of rainfall within a five consecutive days period. The sowing window was kept between 15 March and 31 May to ensure early sowing of the crop as near to the onset of the rainy season as recommended by Allan (1972).

With this set-up, the growth and yield of maize H6302 was simulated for the year 1977 which was one of the years when observed daily weather data of sufficient quality were available. The crop was planted on April 28 with a basal dressing of 30 kg N ha^{-1} and 110 kg N ha^{-1} at 35 days post emergence (d.p.e) and the crop was kept weed free according to the management used by Cooper (1979). The simulated dry matter accumulation, leaf area and grain yield were compared with those observed by Cooper (1979) and are presented in Table 1.

Treatments simulated

We examined a factorial combination of eight levels of N application and three levels of weed control. This provided a factorial 24 treatments, which is probably more than would be advocated in field experimentation but is one advantage of the use of a crop growth simulation model where specific treatments can be investigated at this level of detail without the corresponding costs associated with field work. Apart from the control with no N application, N was applied as a basal dressing of 30 kg ha^{-1} to all treatments, with additional top dressings of 0, 30, 60, 90, 120, 150 and 180 kg N ha^{-1} providing the eight levels of 0, 30, 60, 90, 120, 150, 180 and 210 kg N ha^{-1}. The three weed control treatments were (i) 'no weeding' apart from that achieved through seedbed preparation and planting operations, (ii) 'weed free' which simulated a pre-emergence spray of the herbicide atrazine (4 kg ha^{-1} active ingredient) and (iii) weeding at five weeks post emergence (w.p.e). Weeds were allowed to regrow between 5 w.p.e and maturity. In the weed treatments (i) and (iii) weed population was set at 24 plants m^{-2} and, similar to other weed simulation studies at Kitale (Chikowo *et al.*, 2008), the 'summer grass' weed option of APSIM was chosen.

As a second study, we examined the effect of plant population density under a single management combination of current recommendations for N application (30+ 120 kg N ha^{-1}) and weed control (at 5 w.p.e). Maize yield responses to plant populations of 10, 20, 30, 40, 50 and 60 thousand plants ha^{-1} were examined by keeping the between row spacing at 75 cm as currently recommended and varying the within row spacing to achieve the desired population.

Partial budget analyses

Rates of return to both N application and to weed control at 5 w.p.e were investigated. Using an exchange rate of 75 Kenya Shillings to 1 US$ and current fertilizer and maize prices, 1 kg of N applied was priced at 2.86 US $ kg N^{-1} and 1 kg of maize grain was valued at $ 0.252 kg^{-1}. Labour for fertilizer application was not costed.

Based on a requirement of 20 person days ha^{-1} for weeding (Jama *et al.*, 1998) and the current government minimum daily minimum wage for Western Kenya of $3.5 day^{-1}, the cost of weeding at 5 w.p.e was set at $70 ha^{-1}.

Table 1. Observed (Cooper, 1979) and simulated (APSIM) growth of maize H6302 at Kitale, 1977.

	Days post 75% emergence		
Total dry matter (kg ha^{-1})	59 12th visible leaf	98 50% tasselling	180 Crop maturity
Observed	3832	12 394	19 740
Simulated	3169	11 036	20 377
Leaf area index			
Observed	2.06	2.52	–
Simulated	1.51	2.36	–
Grain yield (kg ha^{-1})			
Observed	–	–	8 800
Simulated	–	–	8 640
Harvest index			
Observed	–	–	0.445
Simulated	–	–	0.424

RESULTS

Calibration of APSIM

Given the similarity of H614 and H6302 in terms of morphology, maturity length and yield potential together with the fact that the abstracted data (Cooper, 1979) were used to adjust thermal times to obtain the best fit with observed data, the good agreement between observed and simulated data (Table 1) was to be expected, but nevertheless is encouraging.

It was noted from this and subsequent simulations that, as set up in this study, APSIM tended to underestimate the rate of early growth of H6302. This is reflected in total dry matter production and leaf area development at 59 d.p.e. (Table1). Cooper and Law (1977) reported dry matter production at 5 w.p.e for H613C for 16 trials over the period 1972–1976 which ranged from 264 to 885 kg ha^{-1}. In this calibration, dry matter at 5 w.p.e was 325 kg ha^{-1}. However, by 50% tassel emergence and at maturity, the agreement between observed and simulated data was good. In spite of the wealth of maize growth and yield data available from Kitale between 1972 and 1977 (i.e. Cooper and Law, 1978b), a more rigorous evaluation of APSIM as calibrated for this study with independent data was not possible due to lack of access to long-term daily weather data for those years. Nevertheless, subsequent simulations (discussed later) closely reflected maize grain yield responses to management reported in the literature.

Comparisons of (i) generated, (ii) observed and (iii) long term mean weather data

We undertook a simple evaluation to ascertain how well the 50 seasons weather data generated by MarkSim represented observed weather data recorded at Kitale, both the long-term averages (FURP, 1987) and the 16 years of daily weather data that we had at hand. Monthly (April–September) mean Tmax, Tmin and solar radiation values and rainfall totals are compared in Table 2 for three data sources.

We first compared long-term average values (FURP, 1987), with average values of the data generated by MarkSim.

Table 2. MarkSim generated, observed (16 years) and long term average weather data for Kitale, Kenya.

Variable	Data source	April	May	June	July	Aug	Sept	Seasonal means and totals
Tmax (°C)	MarkSim	26.0	25.0	24.1	23.4	23.3	24.0	24.3
	Long-term mean (FURP)	25.8	24.8	24.1	23.3	23.7	24.8	24.4
	16 years observed	26.0	25.2	24.2	23.7	24.3	25.3	24.7
Tmin (°C)	MarkSim	13.0	12.8	11.5	11.6	11.0	10.9	11.8
	Long-term mean (FURP)	12.9	12.6	11.7	11.6	11.3	11.0	11.9
	16 years observed	13.2	13.1	12.4	11.6	11.5	11.1	12.1
Radiation (MJ m^{-2} d^{-1})	MarkSim	19.0	17.1	16.9	16.5	16.8	18.9	17.5
	Long-term mean (FURP)	20.5	19.9	19.5	18.2	19.1	20.9	19.7
	16 years observed	n/a	n/a	n/a	n/a	n/a	n/a	–
Total rainfall (mm)	MarkSim	171	207	104	135	132	101	850
	Long-term mean (FURP)	190	198	101	123	151	103	866
	16 years observed	189	153	107	137	150	74	810

FURP: Fertilizer Use Recommendations Project.

The monthly mean values (Tmax and Tmin) and monthly total rainfalls as generated by MarkSim show good agreement with the long-term values (FURP, 1987). However, the radiation values generated by MarkSim are consistently lower across months (approx. 10%) compared with those observed for the long-term average. Dry matter production rates will be affected by levels of radiation. For example, increasing the MarkSim generated radiation value used in the simulations by 10% resulted in a 12.5% increase in dry matter production at 35 d.p.e. However, in the simulation results reported in the rest of this paper, the radiation values were kept as those generated by MarkSim.

We next compared the means of the 16 years of available data with the long-term averages (FURP, 1987). The monthly mean Tmax and Tmin and monthly total rainfall values derived from the 16 years of available observed weather data also compared favourably with the reported long-term (35 year) means (FURP, 1987). With the caveat that this is a comparison of 16 years with the 35-year averages given by FURP, this allows a more detailed comparison rainfall distribution patterns between MarkSim and the 16 years' observed data.

First we looked at the probability distribution of seasonal rainfall totals (Figure 3). The MarkSim generated dataset contained four seasons that were clearly drier than any found in the observed data and one that was wetter. We would note here that the longer the simulated record, the greater the frequency of such 'extremes' is likely to be. However, the distribution of the total rainfalls of the remainder (45 seasons) of the generated dataset corresponded well with observed values.

We then looked at rainfall distribution patterns within the season through a simple comparison of the frequency of rainfall events of different sizes and the frequency of dry spells of different lengths. Differences between mean values for both parameters were tested using a two-tailed *t*-test, having first tested for equal or unequal variance within the two sets of data (Table 3).

Table 3. Comparison of the seasonal (April–September) lengths of dry spells and number of rainfall events of different size from 50 years simulated data (MarkSim) and the observed rainfall data (16 years), Kitale, Kenya.

Average number of rain events per season					
Size of rainfall event (mm)	>0 – < 5	5 – <15	15 – <30	>30	Total events
MarkSim	47.9	29.7	13.7	5.0	96.3
Observed	57.4	32.8	9.3	3.7	103.2
Significant difference between means	$p < 0.01$	$p < 0.01$	$p < 0.05$	$p < 0.05$	*n.s.*
Average number of dry spells per season					
Dry spell length (d)	3–4	5–6	7–8	9–10	>10
MarkSim	4.6	2.4	1.4	0.7	1.4
Observed	5.9	1.5	0.3	0.5	0.3
Significant difference between means	*n.s.*	$p < 0.05$	$p < 0.001$	*n.s.*	$p < 0.001$

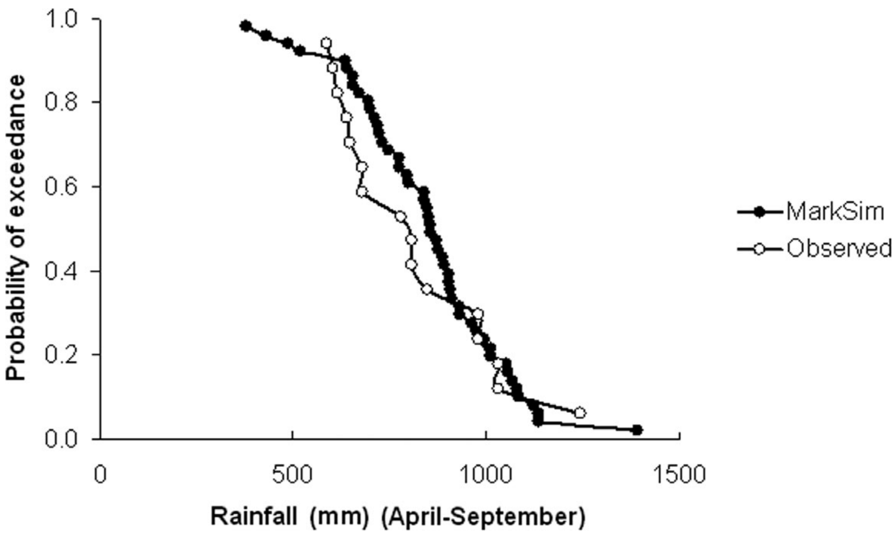

Figure 3. The probability distribution of seasonal rainfall totals (mm) from 16 years observed data and from 50 years simulated data (MarkSim) for Kitale, Kenya.

The MarkSim dataset significantly underestimates the number of days per season with >0 to <5 and 5 to <15 mm of rainfall, and overestimates the number of days with the larger storm sizes of 15 to <30 and >30 mm. The combined results of this latter observation is (i) that there is no significant difference in the total number of rainfall events per season and (ii) MarkSim has generated rainfall totals that are on average higher than those found in the 16 years of observed data (see Table 2 and Figure 3).

Compared with the observed data, MarkSim significantly overestimates dry spells of 5–6, 7–8 and >10 days duration. Given that a greater frequency of longer dry spells is generated by MarkSim, thus providing fewer opportunities for the shorter dry spells, it is not surprising that MarkSim slightly underestimates (though not significantly) the frequency of relatively short dry spells of 3–4 days duration. We further illustrate the

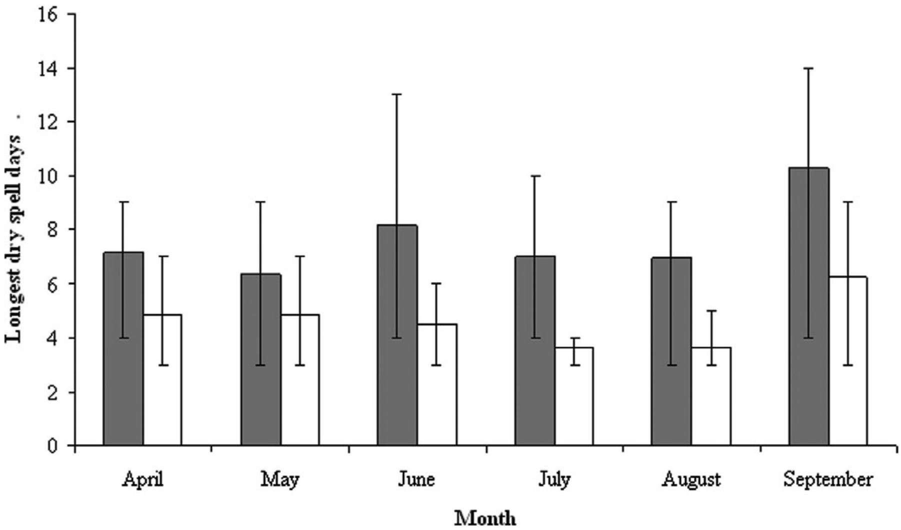

Figure 4. Mean longest dry spell per month for Observed (clear bars) and MarkSim (shaded bars) weather data with the dry spell ranges for 20 and 80% probability exceedance indicated, for Kitale, Kenya

overestimation of longer dry spells by MarkSim through a comparison of the longest dry spells on a monthly basis within the MarkSim and Observed datasets (Figure 4). In this figure we show both the 'average longest dry spell per month', and the range of dry spell values that lie between the 20 and 80% probability of exceedance for each month. MarkSim clearly generates longer dry spells than in the observed data both in terms of means and the range of values generated in all months, as is particularly evident in July and August. We discuss the implications of these long dry spells later in relation to our examination of weather variables that are contributing to risk at Kitale.

An overview of mean maize yield responses to treatments simulated

The mean of the 50 years of simulated maize responses to N-application and weed control were first examined to assess to what extent they corresponded to those reported in previous research (Figure 5). Mean N-responses, both in the weed-free treatment and the weeding at 5 w.p.e increased up to an application of 210 kg N ha^{-1}, but the increases in yield beyond the application of 150 kg N ha^{-1} were small.

The mean rates of returns to N-application were calculated for the 30 N ha^{-1} increments in the 'weeding at 5 w.p.e' treatment since this weed control measure is more likely to be used by small-scale farmers than achieving a weed-free condition through the use of a pre-emergence herbicide. It can be seen that beyond a rate of 150, rates of return fell below a value of 2 which would be unlikely to be of interest to risk-averse farmers. This suggests that a recommendation of a split dressing of 30 + 120 kg N ha^{-1} would be 'optimum' and is similar to the 140 kg N ha^{-1} recommended by Allan (1972).

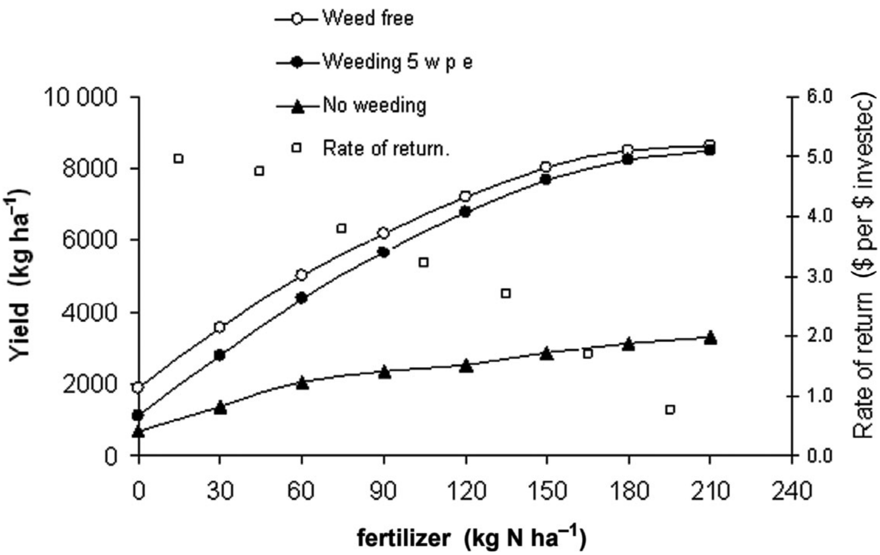

Figure 5. Mean maize yield responses from 50 years of simulations (APSIM) to N application and weed control at Kitale, Kenya.

Controlling weeds through a combination of seed-bed preparation and weeding at 5 w.p.e resulted in a slight depression of the N-response curve below the 'weed-free' scenario, which would be expected. However the yield depression was comparatively small confirming the importance of weeding at 5 w.p.e as reported by Allan (1972). It is interesting to note that the yield depression due to the low levels of weed growth that occurred during the first five weeks, and again between five weeks and maturity, decreased with increasing rates of N-application, suggesting that in such high rainfall environments under this weeding regime, weed competition for N is more important than for water.

The 'no weed control' treatment resulted in substantial yield depression and greatly reduced responses to N-application. This again closely reflects the findings reported by Allan (1972).

We also examined the simulated maize responses to increasing plant populations (Figure 6). Maize yields increased substantially up to a population of 40 000 plants ha^{-1}, but thereafter responses to higher plant populations were negligible. This is very much in line with the current recommendation of planting 180 day hybrid varieties at 44 000 plants ha^{-1} in the Kitale environment (Allan, 1972).

Probability distribution of maize yield responses to N application

The probability distributions of maize yields responses to the different rates of N-fertilizer application were examined for the 50 seasons of simulations (Figure 7). The probability distribution curves for responses to N for fertilizer increments up to 150 kg N ha^{-1} run roughly parallel to each other, indicating that responses to N-fertilizer do not vary a great deal between the lower yield potential seasons and the

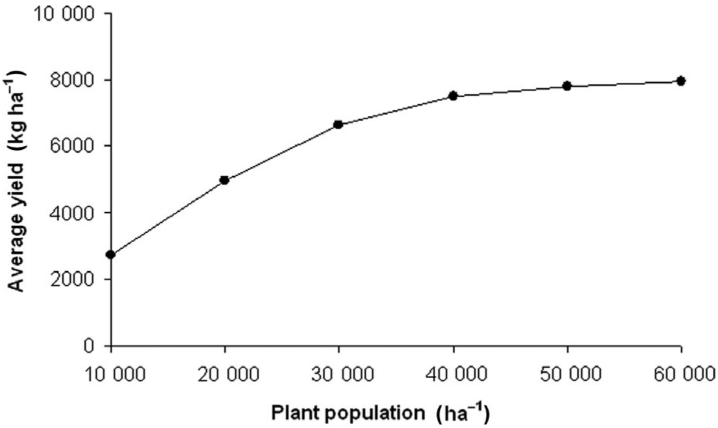

Figure 6. Mean maize yield responses from 50 years of simulations (APSIM) to plant population at Kitale, Kenya.

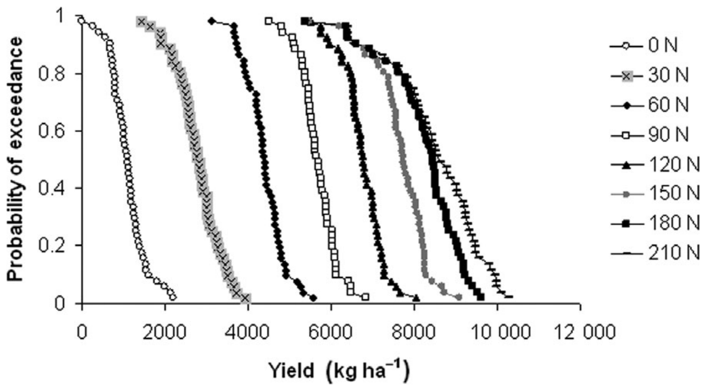

Figure 7. Probability distribution of simulated (APSIM) maize yields at different fertiliser levels (kg N ha^{-1}) with weeding at 5 weeks post emergence at Kitale, Kenya.

higher potential seasons and that there was no interaction between the application of N (at these levels) and the type of season.

For the higher levels of application (180 and 210 kg N ha^{-1}), this picture changes. In the lower potential seasons, i.e at the 90% probability of exceedance, there are no additional responses to high rates of N application, but as the season's yield potential increases at the 5% probability of exceedance, additional responses to higher levels of N application are observed. This is further illustrated in Table 4 where we examined the range of yields, interpolated from Figure 6, that lay between the 95 and 5% probability of exceedance for the different N application rates.

Clearly, the range of yields across different levels of N-application dwarf those found within any rate of application emphasizing the importance of N availability in these high rainfall areas. However, the ranges within a given level of N-applications are also significant. Since the only model input factors to vary from season to season within any rate of N-application are the weather variables associated with temperature, radiation

Table 4. Simulated (APSIM) yield ranges of maize (kg ha^{-1}) lying between the 95 and 5% probability of exceedance at different levels of N-application at Kitale, Kenya.

Fertilizer rate (kg N ha^{-1})	0	30	60	90	120	150	180	210
Yield at 95% exceedance	420	1880	3670	4820	5770	6370	6400	6400
Yield response to each 30 kg N ha^{-1} increment at 95% exceedance	–	1460	1790	1150	948	600	30	0
Yield at 5% exceedance	1970	3620	5250	6450	7540	8680	9380	10 010
Yield response to each 30 kg N ha^{-1} increment at 5% exceedance	–	1650	1630	1200	1090	1140	700	630
Yield range between 95 and 5% exceedance within each fertilizer rate	1550	1740	1580	1630	1770	2310	2980	3610

and rainfall, these must also be impacting on crop growth and yield formation. We examined this in more detail later.

Cooper and Law (1978b) reported maize yields from a range of early planted and 'weed-free' trials conducted between 1972 and 1977 to which 140 kg N ha^{-1} had been added as the standard recommended rate. Over those years, maize yields ranged from 7510 to 9120 kg ha^{-1}. Reference to Figure 6 and Table 4 indicates the good correspondence of the simulated maize yields (150 kg N ha^{-1} applied) and those observed by Cooper and Law.

Rates of return to N-application

In this analysis, we assumed that farmers had applied 30 kg N ha^{-1} as a basal dressing as recommended and then examined the rates of return ($ per $ invested) that a farmer might expect to achieve from subsequent top dressings at 5 w.p.e of 30, 60, 90, 120, 150 and 180 kg N ha^{-1} (Figure 8).

The rates of return achieved for the basal dressing of 30 kg N ha^{-1} were consistently high, exceeding a ratio of 4 in 95% of the seasons. This would be attractive, even for risk-averse farmers and supports the current recommendation for such a basal dressing. Top dressing with a further 30 kg N ha^{-1} seems equally attractive, again exceeding a ratio of nearly 4 in 90% of the seasons. For higher rates of top dressing, the rates of return fell. Whether or not a farmer would choose such higher rates of top dressing would depend on the rate of return required, how many years out of ten would be needed to achieve that rate and the farmer's assessment of the state of the season and crop at 5 w.p.e. This is illustrated further in Table 5 for values interpolated from Figure 8.

The results provided in Table 5 are illustrative of the value of this type of analyses in that they can provide practical guidelines to farmers with contrasting degrees of risk aversion. However, prices of fertilizer and maize can fluctuate greatly from season to season, so sensitivity analyses examining the impact of such price fluctuations could further enhance the value of such information. An example, assuming a 20% increase in the cost of N-fertilizer and a 20% decrease in the value of maize is given (Table 5) to illustrate this.

Table 5. Rates of N top dressing on maize (kg N ha^{-1}) required to achieve contrasting rates of return with different levels of probability of achieving required rate of return, Kitale, Kenya.

Years out of 10 rate of return is required	Minimum rate of return required (N = \$2.86 kg^{-1}: Maize = \$0.252 kg^{-1})					Minimum rate of return required (N = \$3.43 kg^{-1}: Maize = \$0.202 kg^{-1})				
	1	2	3	4	5	1	2	3	4	5
9	180	150	120	0	0	180	120	0	0	0
7	180	180	150	60	0	180	150	0	0	0
5	180	180	150	90	30	180	150	30	0	0

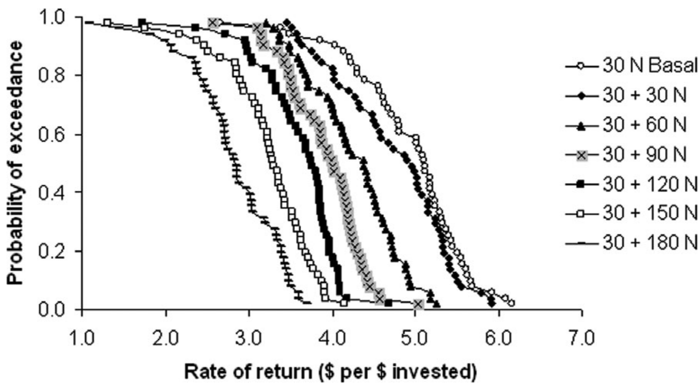

Figure 8. Probability distribution of rates of return (\$ per \$ invested) for different fertilizer levels (kg N ha^{-1}) with weeding at 5 weeks post emergence at Kitale, Kenya.

Rates of return to hand weeding at 5 w.p.e.

The probabilities of exceedance of rates of return to hand weeding at 5 w.p.e at different levels of N application are shown in Figure 9. Clearly, when N fertilizer is applied, weeding is both essential with regard to maintaining yield potential (see Figure 5) and highly profitable in terms of rates of return to labour costs, ranging between 5 and 35 in 90% of seasons across all fertilizer levels. Only in the absence of N fertilizer applications were they marginal in that in the 30% lower potential seasons, rates of return fell below 1.

Probability of maize yield responses to plant population

Mean simulated maize yield responses to increasing plant population (Figure 6) closely reflect those found in field studies and current recommendations. They are illustrated as probabilities in Figure 10 for the current recommendation of 150 kg N ha^{-1} and with weeding at 5 w.p.e. The range of yields simulated within the low plant population of 10 000 plants ha^{-1} is small compared with higher plant populations, indicating that low plant population is the main limiting factor rather than weather variables. However as plant populations increase and become less of a constraint to yield potential, weather variables play an increasing role and as a result the yield range increases.

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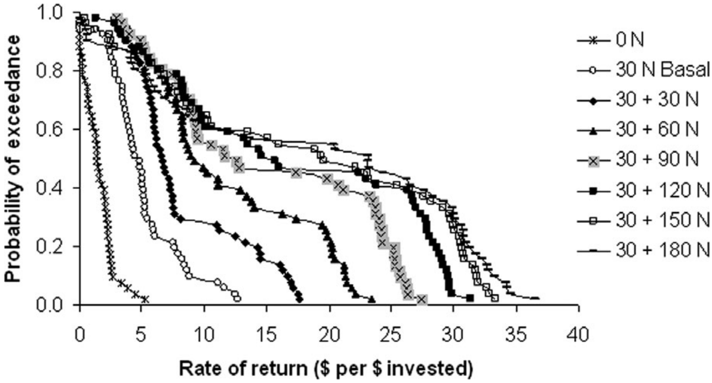

Figure 9. Probability distribution of rate of returns ($ per $ invested) to weeding at 5 weeks post emergence, Kitale, Kenya.

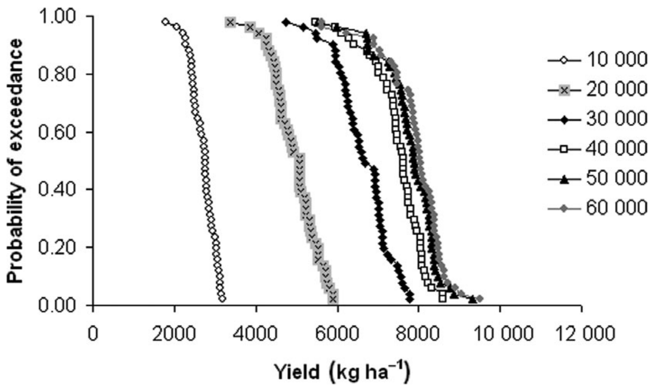

Figure 10. Probability distribution of simulated (APSIM) maize yields at different plant populations (000's ha^{-1}) with 150 kg N ha^{-1} and weeding at 5 weeks post emergence at Kitale, Kenya.

Rates of return to planting extra seed to achieve increasing plant population are very high indeed and are not examined in detail. The current hybrid maize seed price from Kenya Seed Company is $37 per 25 kg bag. Assuming a 1000-grain weight of 420 g (Cooper and Law, 1977), an increase of 10 000 plants ha^{-1} requires 4.2 kg additional seed costing $6.2. With a maize value of $ 0.252 kg^{-1}, only an additional 25 kg ha^{-1} of yield is required to cover those costs. Even allowing for the extra labour required for planting more seeds per hectare, there is no risk involved in planting at the recommended population of 44 000 plants ha^{-1} in such a high potential environment.

The influence of weather factors on maize growth and yield

APSIM simulates the main effects, and their interactions, of air temperatures, radiation levels and available water in discrete soil layers on the rate of maize development, dry matter accumulation and final grain yield in daily time steps and through a complex series of interrelated process sub-models. The purpose of our simple analysis is not to try to duplicate the level of sophistication of such procedures,

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but to approximate the model output by simple linear relationships in order to explore the relative importance of weather variables in contributing to climate risk at Kitale. To undertake this analysis, we simulated maize growth using the 50 years of weather data generated by MarkSim, but set the APSIM simulations under 'nutrient non-limiting' and weed-free conditions to ensure that the influence of weather variables were separated from other effects. We examined the crop growth rates (CGRs) in four distinct phases of crop growth namely: (i) 0–40 d.p.e., corresponding to early exponential growth, (ii) 40–80 days d.p.e, corresponding to the linear phase of vegetative growth, (iii) 80–120 days d.p.e, corresponding to the period of flowering and seed set and (iv) 120–160 days d.p.e, corresponding to the linear phase of grain filling. For each time period, the analysis related the CGR simulated during the period for each of the 50 years to mean air temperatures, mean radiation levels and to the mean water stress index (WSI), an APSIM output which ranges between 0 and 1, and is the index of actual water uptake from the soil, summed over all soil layers, relative to potential biomass growth demand for water on a day. Thus a value of 1 is attained when there is no water stress.

In addition, the biomass at the start of the period being examined was included as a variable since that reflects the 'starting potential' for subsequent biomass production in the following period. Thus for any given time period:

$$\mathrm{CGR} = (f_1) \times (\mathrm{B}) + (f_2) \times (\mathrm{T}) + (f_3) \times (\mathrm{R}) + (f_4) \times (\mathrm{WSI})$$

where:

CGR = crop growth rate in kg ha^{-1} day^{-1}
B = biomass at start of the period in kg ha^{-1}
T = mean air temperature for the period in °C
R = mean radiation during the period in MJ m^{-2} day^{-1}
WSI = mean water stress index for the period.

The highest and lowest mean values of the variables under consideration are shown for the four crop growth stages in Table 6 to indicate the ranges encountered in this study and regression equations obtained are given in Table 7.

In the 0–40 d.p.e period, the mean crop growth rates for the 50 years were positively influenced by a favourable water supply (i.e. a high WSI value), high radiation levels and warm temperatures. This reflects what has been shown in field studies (Cooper and Law, 1977). During this period, rapid production of leaf area is essential and will be driven by the effect of temperature on (i) the leaf emergence rate and (ii) the rate of photosynthesis. Clearly, high radiation levels will also promote high rates of dry matter production. During this period, root growth is largely restricted to the 0–15cm soil depth interval, a fact that APSIM builds into the calculation of the WSI factor. Thus relatively short dry spells leading to soil surface drying will have pronounced negative effects on crop growth. As the crop started to enter its linear phase of vegetative growth (40–80 d.p.e), the biomass at the start of the growth period became the major factor determining subsequent potential crop growth rates, but this was modified by the levels

Table 6. Range of values in the four growth periods of simulated (APSIM) maize growth at Kitale, Kenya.

Crop growth period (d.p.e)		0–40	40–80	80–120	120–160
Crop growth rate (kg ha^{-1} d^{-1})	Highest	20.4	214	364	506
	Lowest	2.3	88	201	268
Dry matter at start (kg ha^{-1})	Highest	0	817	8566	14 590
	Lowest	0	93	3534	8045
Mean air temperature (°C)	Highest	21.1	20.7	21.3	20.2
	Lowest	15.9	15.5	14.2	15.5
Mean radiation (MJ m^{-2} d^{-1})	Highest	22.2	21.2	21.8	24.1
	Lowest	13.2	12.8	12.0	13.8
Mean WSI	Highest	1.0	1.00	1.00	1.00
	Lowest	0.62	0.85	0.89	0.87

WSI: water stress index.

Table 7. Linear regression equations relating simulated crop growth rates (CGR) to weather variables and biomass for four growth periods at Kitale, Kenya.

Time period (d.p.e)	Multiple linear regression equation	R^2-value
0–40	CGR = −41.9 + 22.4WSI** +0.75R** + 0.90T*	0.42
40–80	CGR = 34.4 + 0.11B** + 3.90R*	0.54
80–120	CGR = −138 + 0.031B** + 265WSI*	0.78
120–160	CGR = −338 + 0.026B** + 455WSI*	0.80

** $p < 0.01$; * $p < 0.05$.
WSI: water stress index.

of radiation that the crop received. In the subsequent periods (80–120 and 120–160 d.p.e), the biomass at the start of the period continued to be the dominant factor setting the potential for crop growth rates during the period, but in both these periods, water stress (i.e. low WSI values) was shown to limit growth. In other words, high crop growth rates during early growth are important in setting the potential for subsequent growth and yield development of maize at Kitale. This is consistent with field-based results and is discussed later. We note here however, that whilst simple linear relationships have identified key weather variables influencing crop growth rates, their limitation in reflecting the complex interactions of temperature, radiation and moisture supply is indicated by the unexplained variation which, in these simulations is still due to weather.

DISCUSSION

It is beyond the scope of this paper to undertake a detailed statistical comparison between the weather data simulated by MarkSim, the long-term averages and the 16 years of daily data at hand, although such studies have been undertaken comparing the performance of a range of available weather generators (e.g. Hartkamp *et al.*, 2003). For the purpose of this paper, we have endeavoured to show that the 50 years of generated weather data was a sufficiently close approximation to the weather data that we had at hand to allow its use as an input into APSIM. The monthly means (temperature) and totals (rainfall) (Table 2) generated by MarkSim were in close agreement with observed data, but the generated radiation levels were consistently about 10% lower than the long-term averages. The average total number of rainy days per season and the distribution of rainfall events of different sizes (Table 3) generated by MarkSim were also in good agreement with those observed in daily data at hand. The greatest discrepancy lay in the comparison of the frequency of dry spells (Table 3 and Figure 4) where it was observed that MarkSim generated many more dry spells of greater than 10 days than existed in the observed data. The bulk of these long dry spells occurred towards the end of the rainy season during late August / early September, but others occurred during June and at the start of the rains in April. Although these were not noted in the 16 years observed data, Cooper and Law (1978b) noted periods of up to 20 days with very low rainfall totals (<10mm) at Kitale at the start of the rains between 1973 and 1975. Overall, we feel that for the purposes of use in crop simulation models, and if long-term daily weather data is not available, the MarkSim generated daily data for Kitale was of sufficient quality, reflecting the conclusions of Hartkamp *et al.* (2003). This is also borne out by maize growth and yield outputs generated by APSIM, which closely reflected the results obtained from field-based studies discussed below.

It was fortunate that the calibration of Hybrid 614 already exists within APSIM, that crop growth data were available from Cooper (1979) to adjust that calibration for the very similar Hybrid 6302 and that the required recorded weather data was available for the year in which the field study was undertaken. It was unfortunate, however, that the calibration we achieved could not be more rigorously evaluated by comparing simulated maize yields with those observed in years other than the calibration year for which a wealth of crop growth data exist (Cooper and Law, 1978b). However, this was a particular circumstance to this study. In practice, the added workload to collect the soil, crop and weather data as part of an agronomic field study in order to calibrate and rigorously validate ASPIM is not great, and should not prove a deterrent given the added value that such research can provide in terms of climate risk assessment.

The simulated maize growth and yield and yield responses to the management factors of weed control, planting population and N-fertilizer application closely reflect results of agronomic and crop physiological studies reported from Kitale (Allan, 1972, Cooper and Law, 1977; 1978a;b) and clearly added value to shorter-term field-based studies in that they were able to identify to what extent climate-induced risk might impact on crop management recommendations for such a high rainfall area. This was particularly evident in the case of N-application where the rates of return where shown to vary considerably both across and within any given rate of N-application (Figure 8), depending on the yield potential of different seasons. For example, for the currently recommended application of 150 kg N ha^{-1}, the rates of return ranged from 1.6 to 4.7. Naturally, in drier environments such as the SAT, where moisture supply is both lower and a great deal more variable, rates of return will also vary a great deal more. For example, in the semi-arid tropics of Zimbabwe, they can range from −8 to +12 for rates of N-applications of between 17 and 52 kg N ha^{-1} (Dimes, 2005). Nevertheless, knowledge of such risk associated with fertilizer use is still of great value in high rainfall areas as risk aversion will vary from farmer to farmer, depending on their circumstances. Being able to tailor fertilizer recommendations more specifically to individual farmer's risk aversion whilst also taking into account fertilizer and maize price fluctuations should clearly be of value (Table 5). This should be especially useful with regard to the top dressing of N at 5 w.p.e as by that stage farmers will have a good feel for how the season has developed and the state of their crops. Such knowledge is likely to affect the level of risk that an individual would be prepared to accept in any given season.

Our simple investigation into which weather parameters were playing a role in causing 'weather-induced risk' also reflect the results of studies undertaken at Kitale between 1972 and 1977. Cooper and Law (1977; 1978a) reported results which concentrated on weather variables affecting the early growth of maize between 0 and 35 d.p.e. From results obtained from 12 trials undertaken in 1973, 1974 and 1975, they established the relationship:

$$W_5 = 6.27T^{**} - 0.33N^{**} - 93.6\ (R^2 = 0.88)$$

where W_5 = the weight of the plant at five weeks (g pl^{-1}), T = the mean air temperature (°C) and N = the number of days the 0–15 cm soil horizon was at or below wilting point and ** $p < 0.01$. Those results reflect the results obtained in this study where moisture stress and air temperatures were also found to be important in determining early dry matter production rates. Unlike Cooper and Law, this study also suggested that radiation was a limiting factor during early growth. However, during the early growth periods in the Cooper and Law years of study, mean radiation levels for the early growth period ranged from 18.6 to 23.1 MJ m^{-2} d^{-1}, whilst in this simulation study, they fell much lower with mean values ranging from 13.2 to 22.2 MJ m^{-2} d^{-1}. (Table 6).

Cooper and Law (1977) also concluded that at Kitale, the rate of early growth was very important in setting the yield potential of the crop and, for the years under study, were able to establish a linear relationship between the weight of the plant at five weeks and the final grain yield. However, during those years, concurrent moisture studies (Cooper and Law, 1978b) indicated that no prolonged dry spells of >10 days occurred and there was no moisture stress during vegetative growth and grain filling. We were unable to establish a relationship of dry matter produced by 40 d.p.e and final grain yield. However in these simulations our analyses showed that both low radiation levels (40–80 d.p.e) and moisture stress (80–160 d.p.e) had negative impacts on the yield potential set during early growth (Table 7). However, this study did show that the initial biomass at the start of each growth period from 40 d.p.e onwards was the most significant factor determining subsequent crop growth rates (Table 7), confirming that the potential set during early growth had a continuing role in determining final grain yield.

CONCLUSIONS

Whilst weather-induced risk in this high potential maize growing environment is clearly not as great as that likely to be experienced in more arid locations and was shown not to be important in influencing recommendations for sowing rates and weed control, it is still a factor that clearly influences the rates of return and hence risk associated with N fertilizer use. As such the type of climate risk analyses that we have demonstrated in this study has value. This is especially true since (i) such high potential environments tend to be the 'bread baskets' that ensure national food security and (ii) that widespread N deficiency is recognized as a major constraint to crop production in SSA. Crop growth simulation models such as APSIM, when driven by sufficient years of long-term weather data, have an important role in quantifying such climate-induced risk. Availability of long-term daily weather data is likely to remain a serious constraint and our study has shown that weather generators such as MarkSim can play an invaluable role in this respect. However, we would caution against using such weather generators without some form of comparison of their output with, at the very least, long-term monthly mean weather data from a nearby recording station. Finally, in an era when increasing attention is being given to climate-induced risk and rainfed agriculture, and possible changes in the nature of that risk as a result of climate change, we would make a plea for greater collaboration between agricultural and meteorological services in Africa and for greater ease of access to historical weather records.

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